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Revisions in concurrent seasonal adjustments of daily and weekly economic time series*

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Abstract

The COVID-19 outbreak in 2020 has fostered in many countries the development of new weekly economic indices for the timely tracking of pandemic-related turmoils and other forms of rapid economic changes. Such indices often utilise information from daily and weekly economic time series that normally exhibit complex forms of seasonal behaviour. The latter dynamics were initially removed with ad hoc or experimental methods due to the urgent need of instant results and hence the lack of time for inventing and approving more sophisticated alternatives. This, nevertheless, has in turn inspired recent developments of seasonal adjustment methods tailored to the specifics of infra-monthly time series. Although sound theoretical descriptions of these tailored methods are already available, their performance has not been evaluated empirically in great detail so far. To fill this gap, we consider real-time data vintages of several infra-monthly economic time series for Germany and analyse the cross-vintage stability of holiday-related deterministic pretreatment effects as well as the revisions in various concurrent signal estimates obtained with experimental STL-based and selected elaborate methods, such as the extended ARIMA model-based and X-11 approaches. Our main findings are that the tailored methods tend to outperform the experimental ones in terms of computational speed, that the considered pretreatment routines yield generally stable parameter estimates across data vintages, and that the extended ARIMA model-based approach generates the smallest and least volatile revisions in many cases.

Keywords: extended ARIMA model-based approach, extended X-11 approach, Google trends, JDemetra+, real-time analysis, signal extraction, stability analysis, STL approach.

JEL classification: C01, C02, C14, C22, C40, C50.

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1 Motivation

Weekly economic indices have become a well-established tool for monitoring short-term economic developments in many countries in recent years, see [Eraslan and Götz \(2021\)](#), [Fenz and Stix \(2021\)](#), [Lewis, Mertens, Stock, and Trivedi \(2021, 2022\)](#), [Wegmüller, Glocker, and Guggia \(2023\)](#) and [Woloszko \(2024\)](#), amongst others. This index type has shot to fame during the COVID-19 pandemic in 2020 when the timely tracking of rapid economic changes related to the onset of and the policy response to this unprecedented situation was crucial. It often blends information from daily and weekly economic time series that typically display complex forms of seasonal dynamics, such as the coexistence of multiple seasonal patterns with potentially fractional periodicities, see [Ollech \(2023\)](#) and [Proietti and Pedregal \(2023\)](#) for thorough discussions of such data peculiarities. Those seasonal movements usually need to be removed prior to the index calculation, which was initially done with ad hoc or experimental methods that could not fully take all infra-monthly data features into account; under the given circumstances, however, the urgent need for instant results—and therefore the lack of time for devising and approving more sophisticated methods—justified their application.

With the passage of some time, however, several new and more elaborate seasonal adjustment methods tailored to the specifics of infra-monthly time series have been proposed. Prime examples are the TRAMO-like linear regression framework for data pretreatment and the generalisations of the famous ARIMA model-based (AMB) ([Gómez and Maravall, 2001b](#); [Maravall, 1995](#)) and X-11 seasonal adjustment approaches ([Shiskin, Young, and Musgrave, 1967](#)) for monthly and quarterly data. These generalised modelling and seasonal adjustment methods have been implemented in the latest version branch of the JDemetra+ (JD+) time series software that has been recommended by Eurostat and the European Central Bank for usage in official statistics within the European Statistical System and the European System of Central Banks since February 2015. This new JD+ version also implements the classic STL method ([Cleveland, Cleveland, McRae, and Terpenning, 1990](#)) and core routines for structural time series models ([Harvey, 1989](#)); detailed descriptions of the software are given in [Webel \(2022\)](#) and [Webel and Smyk \(2024\)](#).

Such theoretical advances notwithstanding, the new and tailored seasonal adjustment methods still require thorough assessment, testing and empirical comparisons with experimental benchmark methods, which is not currently available. To fill this gap, we conduct a real-time revision analysis that focuses on two main sources of revisions in seasonally adjusted estimates: data revisions and technical (filtering) revisions, see [Pierce \(1981\)](#) for a general discussion. For the time being, we study their joint effect since this is what users of seasonally adjusted data typically experience; more specifically, we analyse the cross-vintage stability of holiday-related deterministic pretreatment effects and the revisions in various concurrent signal estimates obtained with an experimental STL-based method called the DSA approach ([Ollech, 2021](#)) and the extended AMB and X-11 approaches, using real-time data vintages of several infra-monthly economic time series for Germany. Studying (quasi-)real-time revision profiles of both seasonal and seasonally adjusted estimates has a long history in the empirical assessment of seasonal adjustment methods for monthly and quarterly time series; for example, [Dagum \(1982a,b, 1983, 1987\)](#), [Dagum and Laniel \(1987\)](#), [Dagum and Morry \(1984, 1985\)](#), [Deutsche Bundesbank \(2011\)](#), [Huot, Chiu, Higginson, and Gait \(1986\)](#), [Kenny and Durbin \(1982\)](#), [McKenzie \(1984\)](#), [Pierce](#)

(1980), [Pierce and McKenzie \(1987\)](#) and [Wallis \(1982\)](#) analyse revisions in classic X-11 seasonal adjustments while [Maravall \(1986\)](#), [McElroy and Gagnon \(2008\)](#) and [Planas and Depoutot \(2002\)](#), amongst others, conduct similar research for the classic AMB approach.

The remainder is organised as follows. After a brief data description in [Section 2](#), we introduce the basic modelling framework and define the requisite revision measures in [Section 3](#). The results of our real-time revision analysis are reported in [Section 4](#), including an assessment of computation times. We conclude with a summary and some final remarks for future research in [Section 5](#).

2 Data

We consider five daily and one weekly time series with pronounced seasonal behaviour that enter the PCA-based calculation of the weekly activity index (WAI) for the German economy ([Eraslan and Götz, 2021](#)). The unadjusted data is taken from the weekly vintages processed by the Bundesbank when running experimental DSA seasonal adjustments over the 2022 W01 through 2024 W01 period. New vintages are released on Mondays except for the daily truck toll mileage index for which new observations become available every Thursday. Each new vintage will thus contain one additional observation for the weekly series and seven new observations on average for the daily series. Deviations from this average usually result from delayed recordings due to public holidays around the weekend.¹

[Figure 1](#) shows the six WAI component series as released in the 2022 W01 vintage, revealing the presence of repetitive annual movements especially in the five daily series. These movements will be called day-of-the-year (DOY) and week-of-the-year (WOY) patterns. The COVID-19 lock-downs from 22 March through 4 May 2020 and from mid-December 2020 through May 2021 are also clearly visible, especially in the weekly Google trends and daily pedestrian counts and total flights series. [Figure 2](#) shows a plot of the estimated spectral density (in decibels) against log-frequency for each WAI component series; the presence of the aforementioned DOY and WOY movements is confirmed as the respective estimates display local peaks at (some of) the corresponding seasonal frequencies, see, for instance, the spectral peaks at the fundamental DOY frequency and some of its harmonics for daily electricity consumption. What is more, however, the look from this spectral perspective also unmasks the presence of even stronger infra-weekly recurring dynamics in each daily series, which will be referred to as the day-of-the-week (DOW) pattern; this presence is indicated by the three high and narrow peaks in the estimated spectral densities at the DOW frequencies. Overall, presence of complex seasonal movements is a common facet of the six WAI component series for which we next provide some background information, see also [Table 1](#).

Air pollution (AP, daily) Air pollution is defined as the concentration of nitrogen dioxide (NO₂) in units of micrograms per cubic metre ($\mu\text{g}/\text{m}^3$) averaged across all available measurement stations in Germany. Measurements are currently taken at more than 500

¹For example, the 2023 W15 vintage contains only three new observations (3–5 April) for daily electricity consumption due to the Easter holidays falling on 6–10 April. Accordingly, the 2023 W16 vintage has 11 new observations.

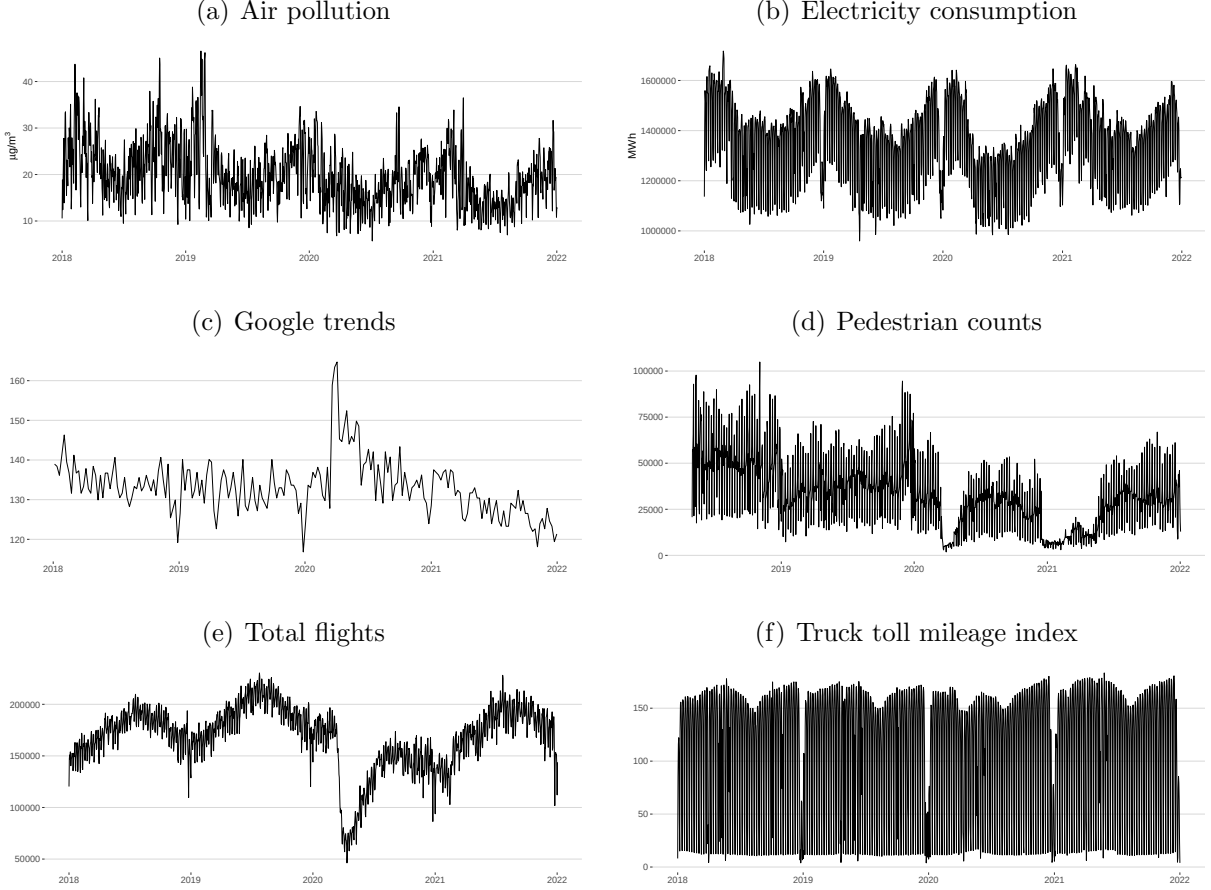


Figure 1: Infra-monthly WAI component series with pronounced seasonality (shown as of 2018 as released in the 2022 W01 vintage).

stations in diverse urban, suburban and rural areas. The AP series is calculated from data published by the German Environment Agency.

Electricity consumption (EC, daily) Realised electricity consumption is considered in units of megawatt hours (MWh) and covers electricity supplied to the network for the general supply, excluding electricity supplied to the railroad network and to internal industrial and closed distribution networks as well as electricity consumed by the producers. The EC data are provided by the Federal Network Agency.

Google trends (GT, weekly) Google trends cover weekly search activity for the term “Arbeitslosigkeit”—the German translation of unemployment—from Sunday through Saturday. Owing to Google’s download restrictions regarding sample size, non-overlapping 5-year sequences of weekly observations are downloaded first, with the maximum observations being normalised to 100 within each sequence. Those sequences are then padded and rescaled using a 20-year monthly benchmark series to form long weekly GT series with values ranging between 100 and 200.

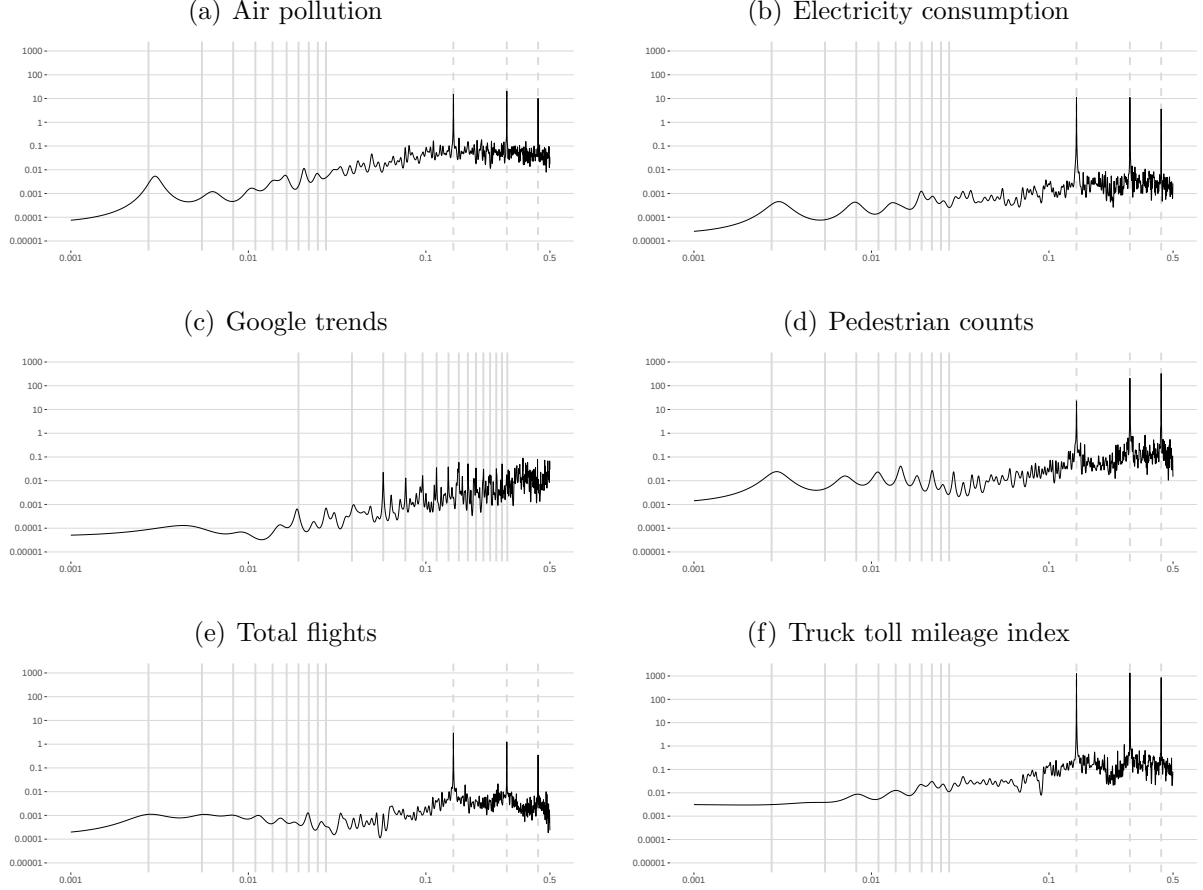


Figure 2: Autoregressive estimates for the spectral density of the differenced logged infra-monthly WAI component series (2022 W01 vintage). Verticals mark selected day/week-of-the-year frequencies (*solid lines*) and the three day-of-the-week frequencies (*dashed lines*).

Pedestrian counts (PC, daily) Pedestrian counts are a weighted average of the numbers of pedestrians observed in eight major German cities² in preselected spots, such as major shopping streets. These numbers are recorded by Hystreet, a subsidiary of the Cologne-based AC+X Strategic Investments Company, and the weights correspond to the cities' population shares in the year 2018. The PC series has been recalculated as an index (2019 = 100) as of the 2022 W47 vintage; in addition, it has been enlarged to include data from 21 cities as well as re-based (2021 = 100) as of the 2023 W03 vintage. To avoid breaks in the measurement concept, all prior vintages are also transformed to index data (2021 = 100). The PC series was not calculated for the 2022 W52 vintage and is therefore identical to the index released in the 2022 W51 vintage.

Total flights (TF, daily) Total flights are defined as the total number of worldwide flights as recorded by Flightradar24, a global flight tracking service that provides real-time information about more than 200,000 flights from more than 1,200 airlines flying to, or from, more than 4,000 airports around the world. The TF series includes different types

²Berlin, Cologne, Düsseldorf, Frankfurt am Main, Hamburg, Munich, Leipzig, and Stuttgart.

Table 1: Basic information about the infra-monthly WAI component series

Series	AP	EC	GT	PC	TF	TTMI
Start	1 Jan 2016	1 Jan 2015	2004 W02	1 May 2018	1 May 2016	1 Jan 2008
Obs _f	2,194	2,556	939	1,343	2,073	5,115
Obs _l	2,922	3,288	1,043	2,071	2,802	5,843

Note: Obs_f and Obs_l are the numbers of observations in the 2022 W01 and 2024 W01 vintages, respectively.

of commercial flights, such as passenger, cargo and charter flights, as well as private and government flights, gliders, most helicopter and ambulance flights, some military flights, and drones.

Truck toll mileage index (TTMI, daily) The truck toll mileage index measures the distance in kilometres driven by heavy goods vehicles, i.e. trucks with a gross vehicle weight rating of 7.5 tonnes and above, that are subject to toll charges on German federal motorways and trunk roads. The sovereign tasks associated with toll collection are performed by the Federal Office for Goods Transport. Additional insights, including details about the experimental DSA seasonal adjustment of the TTMI series, can be found in [Cox, Triebel, Linz, Fries, Flores, Lorenz, Ollech, Dietrich, LeCrone, and Webel \(2020\)](#).

3 Notations and definitions

Basic UC model Let $\{y_t\}$ denote an infra-monthly time series and assume that it can be decomposed additively into its constituent unobservable components (UC) according to

$$f(y_t) = t_t + s_t + h_t + i_t, \quad (1)$$

where $f(\cdot)$ is a potentially non-linear transformation, $\{t_t\}$ is the trend-cyclical component, $\{s_t\}$ is the seasonal component, $\{h_t\}$ is the holiday component and $\{i_t\}$ is the irregular component. Throughout this paper, $f(\cdot)$ will be either the identity or the log transformation. The former case will be referred to as the additive UC model, whereas the latter case will be referred to as the multiplicative UC model (because in this case the UCs on the original data scale are given by $\exp(t_t)$, $\exp(s_t)$, etc., and hence are linked multiplicatively). The seasonal component in (1) is further assumed to be an additive superimposition of multiple seasonal patterns, that is

$$s_t = \sum_{\tau \in \mathbb{S}} s_t^{(\tau)}, \quad (2)$$

where $\mathbb{S} = \{\tau_1, \tau_2, \dots\}$ is a finite set of seasonal periodicities with $\tau_i \in [2, \infty)$ for all i and $\{s_t^{(\tau)}\}$ denotes the seasonal pattern associated with periodicity τ .

Data linearisation For the sake of brevity, we here focus on the TRAMO-like pre-treatment routine according to its implementation in JD+. This routine utilises a linear

regression model in which the disturbances are driven by what is called the extended Airline model (EAM). The entire model can be written compactly as

$$(1 - B) \prod_{\tau \in \mathbb{S}} (1 - B^\tau) [f(y_t) - \mathbf{x}_t^\top \boldsymbol{\beta}] = (1 - \theta_1 B) \prod_{\tau \in \mathbb{S}} (1 - \theta_\tau B^\tau) \varepsilon_t, \quad (3)$$

where B is the backshift operator, i.e. $By_t = y_{t-1}$, $\mathbf{x}_t$ is a k -dimensional vector of exogenous variables related to outliers and other deterministic (holiday) events at time t , $\boldsymbol{\beta}$ is a k -dimensional vector of unknown regression effects and $\{\varepsilon_t\}$ is zero-mean white noise with finite variance $\sigma_\varepsilon^2 > 0$.

If $\mathbb{S}$ contains fractional seasonal periodicities in (2), then the corresponding powers of the backshift operator in both the seasonal differencing and MA operators in (3) are defined through the first-order Taylor approximation at unity, that is

$$B^\tau \approx (1 - \alpha_\tau) B^{\lfloor \tau \rfloor} + \alpha_\tau B^{\lfloor \tau \rfloor + 1}, \quad (4)$$

where $\lfloor x \rfloor$ is the largest integer not exceeding x and $\alpha_\tau = \tau - \lfloor \tau \rfloor \in [0, 1)$ is the fractional remainder of τ . Since each $(1 - B^\tau)$ factor naturally carries a $(1 - B)$ factor, model (3) is prone to over-differencing. Therefore, we will consider the generalised version

$$(1 - B)^d \prod_{\tau \in \mathbb{S}} S_\tau(B) [f(y_t) - \mathbf{x}_t^\top \boldsymbol{\beta}] = (1 - \theta_1 B) \prod_{\tau \in \mathbb{S}} (1 - \theta_\tau B^\tau) \varepsilon_t, \quad (5)$$

where $d \in \{1, \dots, 1 + |\mathbb{S}|\}$ is the order of non-seasonal differencing and

$$S_\tau(B) = (1 - B^\tau) (1 - B)^{-1} = 1 + B + \dots + B^{\lfloor \tau \rfloor - 1} + \alpha_\tau B^{\lfloor \tau \rfloor} \quad (6)$$

is the seasonal summation operator associated with periodicity τ . Some theoretical properties of model (5) are discussed in [Webel \(2022\)](#) and [Webel and Smyk \(2024\)](#); the latter also suggest a generalisation in which both the seasonal summation operator (6) and the seasonal MA operator in (5) are further factorised into Gegenbauer-type polynomials for the requisite seasonal frequencies. The present study, however, does not consider such an advanced approximation of $(1 - \theta_\tau B^\tau)$ for fractional τ .³

Data linearisation in the DSA approach also utilises a linear regression model; however, there are some key conceptual differences to the JD+ approach. Against the background of our intended revision analysis, the maybe most important one is that the DSA analogue of models (3) and (5) is run on the DOW-adjusted rather than the unadjusted data, see [Ollech \(2021\)](#) and [Appendix A](#) for more details.

Types of revisions Let $\mathbf{v}_i$ be the vintage of the unadjusted data $\{y_t\}$ published in the i -th release period and $\mathbf{V} = (\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_T)$ the corresponding triangular(-type) data array for some finite horizon T . Also, let $\hat{S}_{t|\mathbf{v}_i}$ be the estimated signal of interest at time t using unadjusted data up to the last observation available in $\mathbf{v}_i$. The concurrent and final signal estimates are then denoted by $\hat{S}_{t|\mathbf{v}_{i(t)}}$ and $\hat{S}_{t|\mathbf{v}_T}$, respectively, where $i(t)$ is a function of time that picks the period of the inaugural release of y_t .

³Instead, the seasonal MA operator in (5) is simply rewritten via (4); when $\tau = 365.2425$, for example, this yields the approximation $1 - \theta_{365.2425} (0.7575 B^{365} + 0.2425 B^{366})$.

In general, we consider two types of revisions. The first type measures changes in later signal estimates as a percentage of the concurrent estimates (PCE). More precisely, we define the final and lag- k PCE revisions as the sequences $\{r_t\}$ and $\{r_t(k)\}$ with

$$r_t = 100 \times \frac{\hat{S}_{t|\mathbf{v}_T} - \hat{S}_{t|\mathbf{v}_{i(t)}}}{\hat{S}_{t|\mathbf{v}_{i(t)}}} \quad \text{and} \quad r_t(k) = 100 \times \frac{\hat{S}_{t|\mathbf{v}_{i(t)}+k} - \hat{S}_{t|\mathbf{v}_{i(t)}}}{\hat{S}_{t|\mathbf{v}_{i(t)}}}, \quad (7)$$

respectively. The second revision type measures changes in the period-to-period (P2P) percentage changes between later and concurrent signal estimates. More specifically, the final and lag- k P2P revisions are given by the sequences $\{r_t^\circ\}$ and $\{r_t^\circ(k)\}$ with

$$r_t^\circ = \Delta^\circ \hat{S}_{t|\mathbf{v}_T} - \Delta^\circ \hat{S}_{t|\mathbf{v}_{i(t)}} \quad \text{and} \quad r_t^\circ(k) = \Delta^\circ \hat{S}_{t|\mathbf{v}_{i(t)}+k} - \Delta^\circ \hat{S}_{t|\mathbf{v}_{i(t)}}, \quad (8)$$

where

$$\Delta^\circ \hat{S}_{t|\mathbf{v}_i} = 100 \times \frac{\hat{S}_{t|\mathbf{v}_i} - \hat{S}_{t-1|\mathbf{v}_i}}{\hat{S}_{t-1|\mathbf{v}_i}}.$$

Final and lag- k revisions carry complementary information. The former concern the relatively remote past; their mean and volatility are typically associated with the reliability of concurrent estimates in the sense of measuring systematic bias from and dispersion around final estimates. In contrast, lag- k revisions concern the more recent past; for that reason, they are typically more important—and often painful—for data users who tend to be interested predominantly in the case $k = 1$.

Revision measures Let n be the number of observations in the span chosen for the revision analysis. To quantify size and volatility of revisions, we consider three descriptive statistics: the mean revision (MR), the mean absolute revision (MAR) and the standard deviation (SD) of revisions. These measures (for the final PCE revisions) are given by:

$$\begin{aligned} \text{MR} &= n^{-1} \sum_{t=1}^n r_t, \\ \text{MAR} &= n^{-1} \sum_{t=1}^n |r_t|, \\ \text{SD} &= \sqrt{n^{-1} \sum_{t=1}^n (r_t - \text{MR})^2}, \end{aligned}$$

bearing in mind that they can be defined analogously for the other revision types in (7) and (8). To assess the speed at which preliminary revisions converge to final ones, we consider the rate of convergence (RC), which is defined as the SD ratio between the lag- k and final PCE revisions in (7), i.e.

$$\text{RC}(k) = \frac{\text{SD}[r_t(k)]}{\text{SD}[r_t]}, \quad k \in \{1, 2, \dots\}. \quad (9)$$

Fast (slow) convergence of PCE revisions is indicated by (9) if $RC(k) \rightarrow 1$ for small (large) values of k . Usually, there will be a trade-off between size and speed of convergence of revisions, that is smaller (larger) preliminary PCE revisions typically go along with slower (faster) convergence.

4 Results

Each WAI component series in the 2022 W01 through 2024 W01 vintages is seasonally adjusted with the extended AMB and X-11 approaches as well as the classic STL method implemented in JD+, including data pretreatment with model (5); the five daily series are also seasonally adjusted with the DSA approach. The corresponding specifications are detailed in [Appendix B](#). In short, assuming the multiplicative form of UC model (1), automatic outlier detection and a common set of 17 user-defined holiday variables for Germany is specified in (5) along with $\mathbb{S} = \{7, 365.2425\}$ and $d = 2$ (recall the visual evidence in [Figure 1](#) and [Figure 2](#)); two additional variables marking the start and end of daylight saving time are considered for the EC series whereas only five out of the 17 common variables plus four variables for U.S. federal holidays are considered for the TF series (see also Note 2 in [Table 4](#) below). Seasonal adjustment is mostly carried out with default options and without utilising forecasts of the observations, so that asymmetric signal extraction filters need to be applied for each method near the sample boundaries.

[Section 4.1](#) provides a brief evaluation of computing speed. [Section 4.2](#) then presents the results for the daily WAI component series. These are centred around an empirical comparison of the cross-vintage stability of the parameter estimates obtained from model (5) versus the DSA linearisation step and of the final and lag-1 PCE revisions (7) and P2P revisions (8) in three signal estimates obtained with the aforementioned approaches.⁴ Revisions in the unadjusted data are also considered, but those will turn out to play a minor role (except for the GT series). In general, revisions are calculated over the 2022 W01 to 2022 W52 vintages, with the 2024 W01 vintage serving as the final vintage $\mathbf{v}_T$. [Section 4.3](#) reports the same results for the weekly GT series, considering only the JD+ methods and basically the same strategy for setting up the seasonal adjustment specifications (see again [Appendix B](#) for details); the most notable difference, however, is that pretreatment with model (5) now utilises seven holiday variables for Germany as well as $\mathbb{S} = \{52.18\}$. Afterwards, [Section 4.4](#) closes with some cautionary remarks with respect to the interpretation of our results.

4.1 Computation times

[Table 2](#) reports the average computation times required for data pretreatment and estimation of the seasonal patterns for the six WAI component series. As for the daily data, pretreatment with model (5) typically consumes a large portion of total computation time, ranging from 13 seconds, or 56–99% depending on the seasonal adjustment method, for the AP series to almost 4 minutes, or more than 97%, for the TTMI series. In contrast,

⁴Keep in mind that according to (7) and (8) lag-1 revisions refer to changes in estimated signals obtained from unadjusted data that have been released in adjacent weekly Bundesbank vintages. Those revisions would turn into lag-7 revisions for daily data if these were available in daily vintages, see also the first cautionary remark in [Section 4.4](#).

Table 2: Average computation times for signal extraction from the WAI component series

Series	EAM	Extended AMB			Extended X-11			STL			STL-R			DSA	DSA-R
		DOW	..OY	Total	DOW	..OY	Total	DOW	..OY	Total	DOW	..OY	Total		
AP	12.719	0.039	9.955	22.713	0.011	0.140	12.870	0.004	0.151	12.874	0.048	1.525	14.292	33.635	49.726
EC	21.261	0.032	4.683	25.976	0.011	0.129	21.401	0.007	0.139	21.407	0.053	1.531	22.845	74.840	134.060
GT	0.227		0.054	0.281		0.021	0.248		0.010	0.237		0.076	0.303		
PC	29.636	0.036	16.546	46.219	0.011	0.114	29.761	0.003	0.168	29.807	0.040	1.575	31.251	40.612	69.771
TF	28.672	0.041	26.104	54.816	0.011	0.107	28.790	0.003	0.189	28.864	0.047	1.835	30.554	40.136	47.408
TTMI	232.188	0.054	7.096	239.339	0.023	0.352	232.563	0.011	0.239	232.438	0.115	2.650	234.953	2,760.104	3,735.298

Notes: **1** Average computation times are reported in seconds and have been calculated from the 2022 W01 to 2024 W01 vintages (PC: 2022 W19 to 2024 W01 vintages), using 25 replications within each vintage (TTMI: 5 replications). Average total computation times for the extended AMB, X-11 and STL(-R) approaches are defined as the sum of the average computation times for DOW and DOY extraction and EAM pretreatment. **2** All calculations have been carried out on a 64-bit Windows OS with an Intel Xeon Gold 6338T CPU @ 2.10 GHz and 32.00 GB RAM. **3** The suffix “-R” indicates usage of robustness weights in the STL-based methods. The pattern “..OY” indicates the DOY pattern for daily data and the WOY pattern for weekly data.

Table 3: Revision measures for the unadjusted WAI component series

Series	PCE revisions (7)						P2P revisions (8)					
	$\{r_t\}$			$\{r_t(1)\}$			$\{r_t^\%\}$			$\{r_t^\%(1)\}$		
	MR	MAR	SD	MR	MAR	SD	MR	MAR	SD	MR	MAR	SD
AP	-0.7419	0.8406	0.9903	-0.0703	0.1877	0.8604	0.0303	0.5272	1.3706	-0.0017	0.2578	1.1952
EC	-0.4215	3.9294	4.3062	-0.1131	0.1315	0.8255	-0.0039	1.0573	1.5804	0.0026	0.0828	0.5798
GT	3.5653	3.5723	2.5882	-1.3321	1.8892	1.8984	0.0126	2.2190	3.0619	0.0859	1.9792	3.0325
PC	0.4776	2.5710	3.6536	0.0799	0.0799	0.5240	1.2398	3.5502	6.8696	-0.0121	0.0812	0.6867
TF	-0.0001	0.0001	0.0010	-0.0001	0.0001	0.0010	< 0.0001	0.0002	0.0014	< 0.0001	0.0002	0.0014
TTMI	0.0518	0.0518	0.1624	0.0383	0.0383	0.1573	0.0277	0.1068	0.6347	0.0118	0.0874	0.6034

Note: Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions, which have been calculated from the 2022 W01 to 2022 W52 vintages, with the 2024 W01 vintage being considered the final vintage.

estimation of the seasonal patterns from the linearised data with the JD+ methods is quite fast. For the extended AMB method, DOW and DOY extractions usually take less than 0.1 second and 10 seconds, respectively, except for the relatively short PC and TF series for which DOY extraction tends to be 2–3 times slower. Unsurprisingly, the non-parametric methods operate even faster: both the extended X-11 and the non-robust STL method achieve combined DOW and DOY extraction within less than 0.4 second, whereas the robust STL method requires less than three seconds on average to do this job. In most cases, the DSA approach is noticeably slower than the extended AMB approach, i.e. the slowest JD+ method. The largest discrepancy is measured for the TTMI series, for which even the non-robust DSA method is more than 11 times slower; however, DSA beats the extended AMB method when seasonally adjusting the PC and TF series due to the aforementioned longer DOY extraction times of the latter approach.

The higher computational speed of the JD+ methods may have three main reasons. First, the stochastic representation of seasonality in model (5) is much sparser than the deterministic trigonometric representation employed in the DSA linearisation step. Second, maximum likelihood estimation of model (5) utilises efficient algorithms, such as thin QR matrix factorisations computed through Householder reflections and fast Chandrasekhar-type Kalman filtering recursions established from the model’s state space representation, whereas the DSA linearisation step relies on standard maximum likelihood estimation techniques. Third, automatic outlier detection in model (5) closely follows the robust procedure suggested by Gómez and Maravall (2001a) while the corresponding DSA search routine is based on the less robust procedure derived in Chen and Liu (1993).

Similar statements can be made about the average computation times for seasonally adjusting the weekly GT series. In general, the JD+ methods are very fast, taking barely longer than 0.3 second on average for performing both data pretreatment and estimation of the single WOY pattern. Thereby, the extended X-11 and non-robust STL methods are again slightly faster than the extended AMB and robust STL methods.

4.2 Daily WAI component series

Unadjusted data The revision measures reported in Table 3 reveal that the five daily series exhibit fairly different revision profiles. The TF series is barely revised at all, which makes it a good candidate for assessing the pure effects of so-called technical (filtering) revisions.⁵ At the other end of the spectrum, the AP, EC and PC series display relatively large PCE and P2P revisions; in particular, a high volatility is recorded for the lag-1 revisions of the AP series and for the final revisions of the EC and PC series. Finally, the TTMI series exhibits rather moderate revisions in general.

Pretreatment We now assess the cross-vintage stability of the parameter estimates and their point-wise standard errors obtained from model (5). To this end, we first plot these quantities against the 2022 W01 through 2024 W01 data vintages, see Figure 3 for

⁵Technical revisions are unavoidable revisions in estimated signals—even when the unadjusted data are not revised at all—that result merely from the fact that the concurrent (fully asymmetric) signal extraction filter once applied to the last observation can be successively replaced with a less asymmetric variant and eventually with the symmetric filter as more observations are shipping in at the recent end of the sample span.

the AP series, [Figure 4](#) for the EC series, [Figure 5](#) for the PC series, [Figure 6](#) for the TF series and [Figure 7](#) for the TTMI series. In general, the parameter estimates and their point-wise standard errors are reasonably stable over time; the latter, however, are not robust against residual autocorrelation and heteroskedasticity and hence may be too small. Some estimated holiday effects undergo occasional jumps which often coincide with the inaugural release, or a later revision, of holiday-related observations that affects automatic outlier detection. Using the EC series, we instance two such cases as an illustration (see [Figure 4](#)):

1. *Christmas effects in the 2022 W51 versus W52 vintages:* Panels (p)–(r) reveal sudden jumps in the estimated effects of Christmas Eve, Christmas Day and Boxing Day between the releases of the 2022 W51 and W52 vintages. The latter contains the inaugural release of electricity consumption for the 19–26 December 2022 period; there are no revisions in the unadjusted EC series except for a minor downward correction by 0.3 MWh of the initial record for 18 December 2022. The automatic outlier detection routine identifies eight outliers from either vintage: seven of them are exactly the same but an additive outlier identified at 24 December 2016 from the W51 vintage shifts to 24 December 2018 when re-estimating model (5) from the W52 vintage. As a result, the estimates of the three Christmas-related holiday effects rapidly shrink towards zero (i.e. from -0.143 to -0.071 for Christmas Eve, from -0.226 to -0.190 for Christmas Day and from -0.153 to -0.137 for Boxing Day).
2. *New Year effects in the 2023 W10 versus W11 vintages:* Panels (a) and (s) display another set of unusually large jumps in the estimated holiday effects, this time in those related to New Year’s Day and New Year’s Eve. These jumps occur between the releases of the 2023 W10 and W11 vintages, which mark more or less the middle of a short-lived phase of moderate yet repeated revisions of the unadjusted EC data from December 2022 onwards. The number of automatically detected outliers drops sharply from 10 in the W10 vintage to 5 in the W11 vintage; what is more, four out of the five dropped outliers are additive outliers that have fallen into the seven-day period between Christmas Eve and New Year’s Eve (more specifically, these have been identified at 31 December 2016, 24 December 2018, 27 December 2020 and 31 December 2022). As a result, the estimated New Year effects decline from -0.176 to -0.152 for New Year’s Day and from -0.105 to -0.054 for New Year’s Eve. Interestingly, the estimates of the three Christmas-related holiday effects are less affected as they change only marginally from -0.070 to -0.086 for Christmas Eve, from -0.188 to -0.181 for Christmas Day and from -0.122 to -0.130 for Boxing Day.

The cross-vintage evolution of the estimated holiday effects obtained during the DSA linearisation step is quite similar for all series despite some time-constant moderate differences in the magnitude of some estimates. In particular, the DSA estimates tend to be even slightly more stable over time, rarely exhibiting the sudden jumps seen in some of their EAM counterparts. Finally, the visual evidence also suggests that the estimated MA parameters from (5) show little cross-vintage variation for all series.

Complementing this graphical stability assessment, [Table 4](#) reports the cross-vintage standard deviations of all parameter estimates. Those are generally low and quite similar

Table 4: Cross-vintage standard deviations of the parameters estimates in the linearisation models for the daily WAI component series

Effect	AP			EC			PC			TF			TTMI		
	EAM	DSA	DSA-R	EAM	DSA	DSA-R	EAM	DSA	DSA-R	EAM	DSA	DSA-R	EAM	DSA	DSA-R
NYD	0.0231	0.0085	0.0061	0.0157	0.0045	0.0030	0.0686	0.0371	0.0532	0.0028	0.0092	0.0136	0.0408	0.0064	0.0131
EPI	0.0512	0.0239	0.0300	0.0089	0.0038	0.0040	0.0334	0.0229	0.0179				0.0115	0.0047	0.0149
DST-S				0.0016	0.0011	0.0016									
GOF	0.0105	0.0040	0.0072	0.0011	0.0019	0.0030	0.0757	0.0545	0.0595				0.0106	0.0085	0.0126
EAS										0.0014	0.0013	0.0019			
EAM	0.0190	0.0180	0.0235	0.0010	0.0009	0.0012	0.0370	0.0269	0.0404				0.0057	0.0043	0.0109
LAB	0.0221	0.0218	0.0297	0.0017	0.0052	0.0015	0.0247	0.0121	0.0129				0.0439	0.0250	0.0040
ASC	0.0190	0.0040	0.0091	0.0028	0.0023	0.0025	0.0252	0.0214	0.0311				0.0142	0.0133	0.0158
ASC-F	0.0135	0.0088	0.0110	0.0012	0.0020	0.0018	0.0057	0.0074	0.0063				0.0022	0.0031	0.0031
PEN	0.0064	0.0110	0.0117	0.0021	0.0028	0.0031	0.0177	0.0138	0.0173				0.0032	0.0033	0.0248
CCH	0.0102	0.0131	0.0153	0.0018	0.0016	0.0015	0.0224	0.0173	0.0141				0.0026	0.0028	0.0037
CCH-F	0.0072	0.0139	0.0105	0.0015	0.0024	0.0018	0.0127	0.0132	0.0168				0.0012	0.0022	0.0014
IND										0.0033	0.0031	0.0029			
GUD	0.0104	0.0102	0.0148	0.0026	0.0031	0.0039	0.0246	0.0133	0.0175				0.0229	0.0181	0.0250
DST-E				0.0023	0.0024	0.0046									
RFD-500	0.0075	0.0067	0.0081	0.0022	0.0016	0.0038							0.0039	0.0018	0.0017
ASD	0.0131	0.0189	0.0257	0.0049	0.0044	0.0074	0.0237	0.0159	0.0212				0.0092	0.0027	0.0020
THX										0.0034	0.0047	0.0046			
THX-F										0.0061	0.0023	0.0020			
XME	0.0075	0.0182	0.0219	0.0318	0.0052	0.0042	0.0154	0.0388	0.0735	0.0032	0.0052	0.0058	0.0070	0.0210	0.0377
XMD	0.0110	0.0023	0.0026	0.0230	0.0030	0.0073	0.0393	0.0431	0.0341	0.0038	0.0059	0.0082	0.0100	0.0072	0.0099
BXD	0.0307	0.0183	0.0198	0.0124	0.0008	0.0029	0.0446	0.0648	0.0797	0.0017	0.0021	0.0029	0.0157	0.0032	0.0111
NYE	0.0474	0.0259	0.0217	0.0288	0.0164	0.0017	0.0653	0.0540	0.0605	0.0016	0.0020	0.0024	0.0363	0.0230	0.0266
θ_1	0.0021	0.0048	0.0049	0.0055	0.0129	0.0095	0.0072	0.0157	0.0146	0.0034	0.0097	0.0079	0.0069	0.0007	0.0044
θ_7	0.0015			0.0126			0.0196			0.0144			0.0033		
$\theta_{365.2425}$	0.0011			0.0017			0.0010			0.0016			0.0033		

Notes: **1** Standard deviations have been calculated from the 2022 W01 to 2024 W01 vintages. **2** The considered effects in the upper panel are for the following calendar events: New Year’s Day (NYD), Epiphany (EPI), start of daylight saving time (DST-S), Good Friday (GOF), Easter Sunday (EAS), Easter Monday (EAM), Labour Day (LAB), Ascension (ASC), Ascension Friday (ASC-F), Pentecost Monday (PEN), Corpus Christi (CCH), Corpus Christi Friday (CCH-F), Independence Day (IND), German Unification Day (GUD), end of daylight saving time (DST-E), 500th Reformation Day (RFD-500), All Saints’ Day (ASD), Thanksgiving (THX), Thanksgiving Friday (THX-F), Christmas Eve (XME), Christmas Day (XMD), Boxing Day (BXD) and New Year’s Eve (NYE). **3** The suffix “-R” indicates usage of robustness weights in the STL-based method.

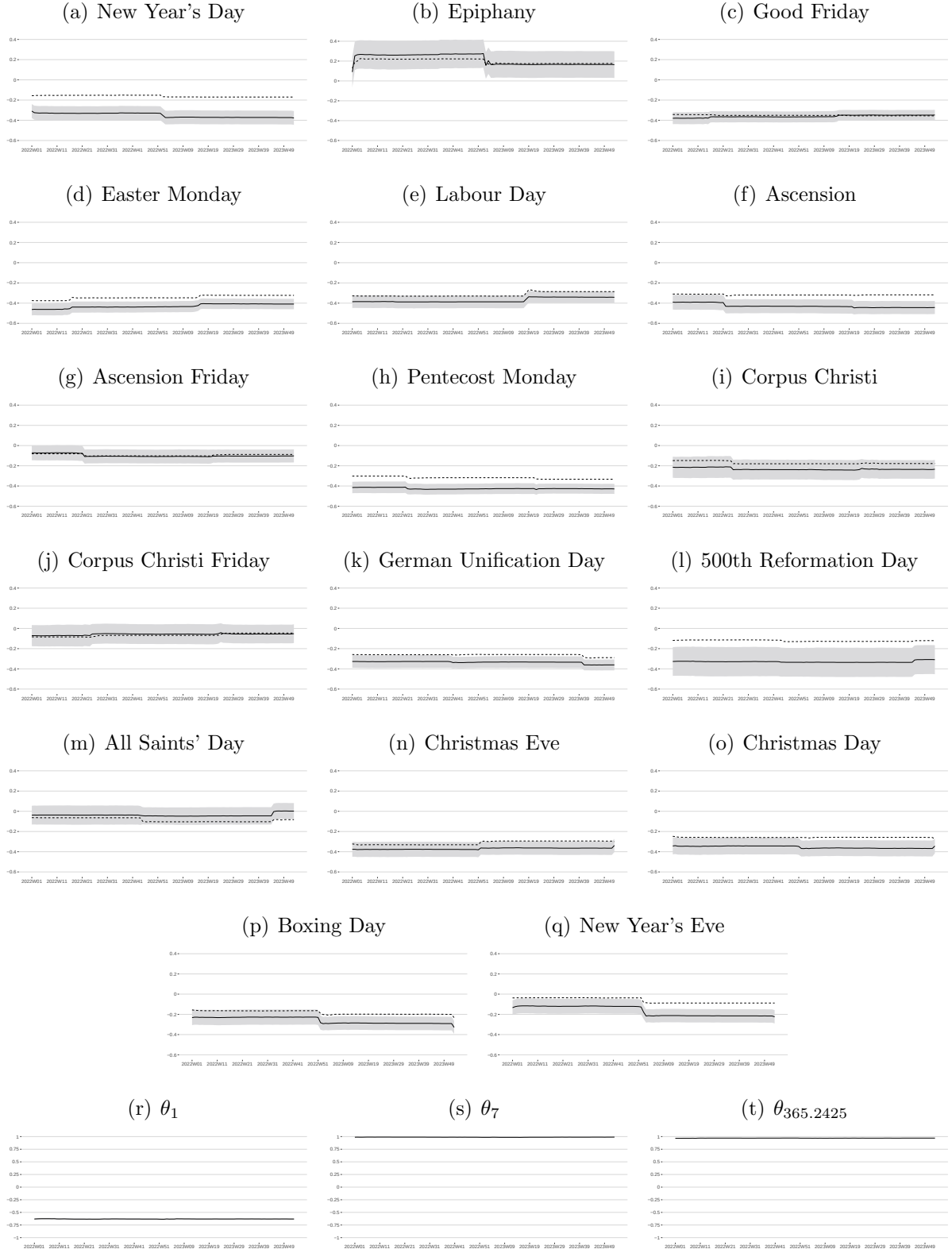


Figure 3: Estimated holiday effects and MA parameters from (5) for the AP series (*solid lines*). Shaded areas mark point-wise ± 1 SE intervals. Dashed lines correspond to estimated holiday effects from the linearisation step of the non-robust DSA variant.



Figure 4: Estimated holiday effects and MA parameters from (5) for the EC series (*solid lines*). Shaded areas mark point-wise ± 1 SE intervals. Dashed lines correspond to estimated holiday effects from the linearisation step of the non-robust DSA variant.



Figure 5: Estimated holiday effects and MA parameters from (5) for the PC series (*solid lines*). Shaded areas mark point-wise ± 1 SE intervals. Dashed lines correspond to estimated holiday effects from the linearisation step of the non-robust DSA variant.

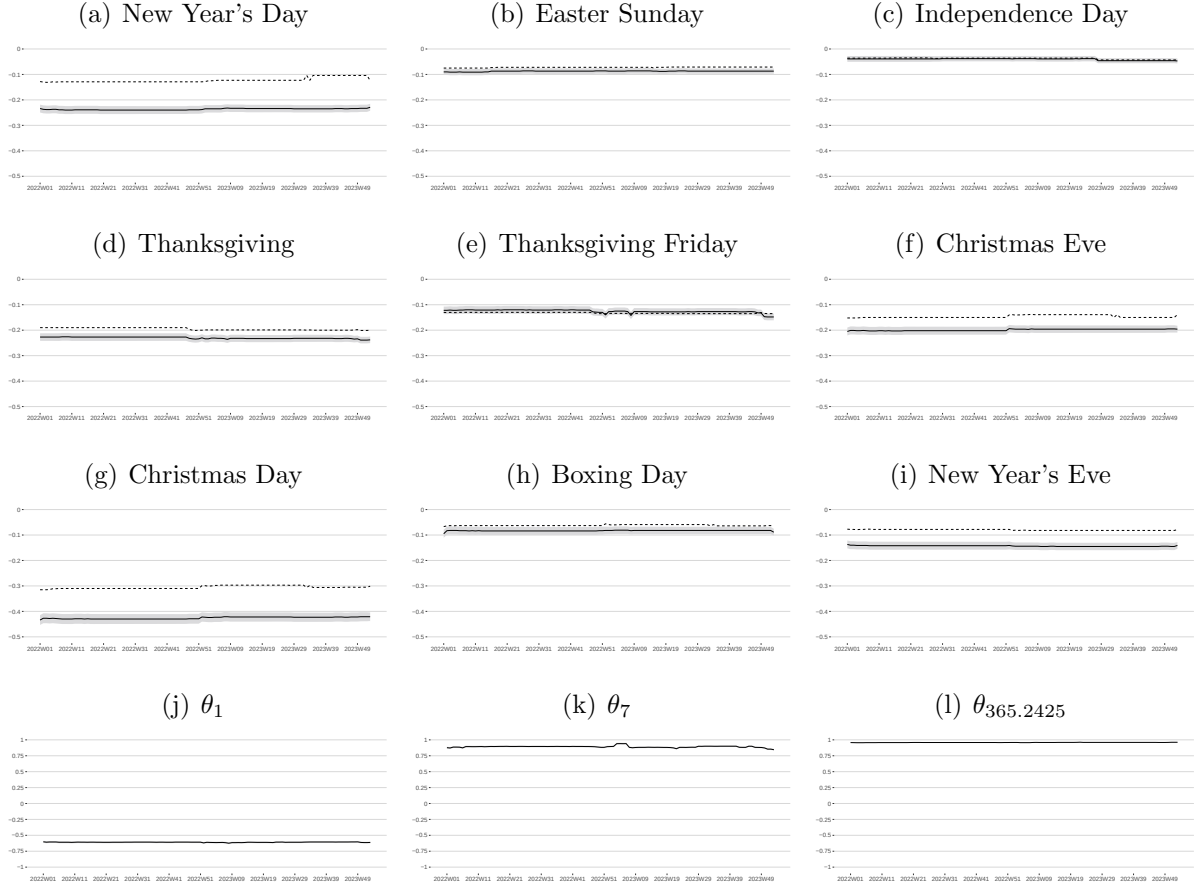


Figure 6: Estimated holiday effects and MA parameters from (5) for the TF series (*solid lines*). Shaded areas mark point-wise ± 1 SE intervals. Dashed lines correspond to estimated holiday effects from the linearisation step of the non-robust DSA variant.

Table 5: Descriptive statistics for the number of automatically detected outliers in the daily WAI component series

Series	EAM				DSA				DSA-R			
	MIN	MAX	AVG	SD	MIN	MAX	AVG	SD	MIN	MAX	AVG	SD
AP	1	2	1.06	0.23	0	0	0.00	0.00	1	2	1.08	0.27
EC	5	10	7.03	1.55	4	6	4.97	0.51	12	21	16.99	2.41
PC	10	13	11.86	0.41	5	6	5.83	0.38	14	18	15.39	0.77
TF	11	14	12.61	0.87	4	6	4.40	0.78	2	6	3.44	0.68
TTMI	56	68	61.63	4.52	66	77	72.50	2.79	101	140	120.92	11.69

Notes: **1** Descriptive statistics are minimum (MIN), maximum (MAX), average (AVG) and standard deviation (SD), which have been calculated from the 2022 W01 to 2024 W01 vintages. **2** The suffix “-R” indicates usage of robustness weights in the STL-based method.



Figure 7: Estimated holiday effects and MA parameters from (5) for the TTMI series (*solid lines*). Shaded areas mark point-wise ± 1 SE intervals. Dashed lines correspond to estimated holiday effects from the linearisation step of the non-robust DSA variant.

between the EAM and DSA estimates, confirming the above findings. As regards model (5), they also reflect the minor instabilities in the estimated holiday effects involved in the aforementioned jump scenarios for the EC series: the standard deviations of the estimated Christmas- and New Year-related effects are significantly higher than those of the other EAM estimates; in contrast, they do not cluster in such a way, or in any other way, for the DSA estimates.

These moderate differences in the outcomes of the JD+ and DSA linearisation steps might be a result of the different orders in which the unobserved components in model (1)–(2) are extracted in the two approaches. In JD+, model (5) is fitted directly to the observations, in line with the classic notion of data pretreatment for monthly and quarterly time series, whereas in DSA the DOW pattern in (2) is extracted first from the observations and then, rather unconventionally, both outlier and holiday effects are estimated from the DOW-adjusted and hence pre-smoothed data (see [Appendix A](#) for more details). From the classic perspective, one might therefore argue that, *ceteris paribus*, the non-robust DSA variant has a proclivity towards leakage of outlying (deterministic non-seasonal) fluctuations into the DOW estimates.⁶ Building upon the arguments made in [Abeln and Jacobs \(2022\)](#) and [Webel and Smyk \(2024, Section 8.3.2\)](#), one might thus suspect that the automatic outlier detection routine in JD+ will tend to find more/not more outliers than the respective DSA routine when STL is run without/with robustness weights. [Table 5](#) provides empirical evidence in favour of this suspicion as it reports selected descriptive cross-vintage statistics for the number of automatically detected outliers. In particular, there are just two exceptions to the suspected rule when comparing the average numbers in the three AVG columns: for the TF series, the JD+ routine finds on average 9 outliers more than the routine in the robust DSA variant; for the TTMI series, the JD+ routine finds on average 11 outliers less than the routine in the non-robust DSA variant. In this regard, it should also be mentioned that either search routine is capable of identifying appropriate sets of (structural break) outliers for an adequate modelling of the sudden level changes related to the COVID-19 lock-downs in the PC and TF series (recall [Figure 1](#)). The pandemic-related effects on the other daily series are more gradual and can thus be captured satisfactorily by the final trend-cycle estimates without outlier modelling.

Signal estimates We now extract the DOW and DOY patterns from each daily series in each data vintage. When performing seasonal adjustment with the four JD+ methods, the two patterns are sequentially extracted from the linearised data, starting with the DOW pattern; recall, however, that in DSA the DOW movements are extracted directly from the observations while the DOY pattern is still estimated from the linearised DOW-adjusted data. Revisions measures are then calculated for the concurrent estimates of the DOW and DOY patterns as well as of the seasonally adjusted (SA) series. These measures are reported in [Table 6](#) for the AP series, in [Table 7](#) for the EC series, in [Table 8](#) for the PC series, in [Table 9](#) for the TF series and in [Table 10](#) for the TTMI series. Our main findings are:

⁶For daily data, one might even go as far as to saying that the holiday component in (1) is technically nothing but a superimposition of cyclical additive outliers with common effects and that its existence, and estimation, merely facilitates interpretation.

Table 6: Revision measures for signal estimates of the AP series

Signal	Method	PCE revisions (7)						P2P revisions (8)					
		$\{r_t\}$			$\{r_t(1)\}$			$\{r_t^\%\}$			$\{r_t^\%(1)\}$		
		MR	MAR	SD	MR	MAR	SD	MR	MAR	SD	MR	MAR	SD
DOW	AMB	0.0077	0.8187	1.0029	0.0019	0.1459	0.1894	-0.1751	1.1862	1.5416	-0.0029	0.1758	0.2283
	X-11	0.0947	3.2296	4.0237	0.0642	2.1925	2.9115	-0.1365	4.0301	5.1402	-0.0186	3.0074	3.9611
	STL	0.1136	3.3301	4.2544	0.0579	1.9308	2.5343	0.0064	4.0019	5.1876	0.0042	2.4194	3.1644
	STL-R	0.2066	4.6625	5.9298	0.0617	2.1882	2.9752	-0.0578	5.7015	7.3397	0.0027	2.8928	3.9714
	DSA	0.1206	3.3975	4.1627	0.0536	1.9284	2.4579	0.0214	4.0966	5.1951	0.0081	2.4260	3.1740
	DSA-R	0.2160	4.8799	6.2020	0.0367	1.9032	2.6260	-0.1184	6.2918	7.9927	-0.0071	2.6954	3.5270
DOY	AMB	-0.0132	0.8456	1.1096	-0.0793	0.7061	0.9139	-0.0024	0.2072	0.3205	0.0001	0.2271	0.5777
	X-11	-0.0232	5.3735	7.5876	-0.0558	2.1325	3.9708	-0.1084	5.5730	8.5015	-0.0653	2.5848	4.9588
	STL	-0.3656	5.7863	7.6786	-0.2545	1.4108	2.8576	-0.0153	4.7719	6.3195	-0.0026	1.0453	1.8696
	STL-R	0.1163	6.8879	10.7423	-0.7297	1.9900	5.3682	-0.1170	8.1432	14.8023	-0.1650	2.6683	7.8864
	DSA	0.6746	5.9582	7.5285	0.0073	0.7901	1.0274	-0.0592	4.6972	6.0406	0.0071	0.8494	1.0994
	DSA-R	0.8875	7.4585	11.7053	-0.0299	1.2967	3.5762	-0.3764	8.7518	15.6825	0.0746	2.0070	7.2289
SA	AMB	-0.6678	1.5122	1.9236	0.0118	0.8220	1.1735	0.0112	1.4986	2.2317	-0.0024	0.4959	1.1611
	X-11	-0.0406	5.9149	8.8292	0.1483	2.6104	4.8069	-0.0001	6.2611	9.9308	-0.0827	3.5358	6.8499
	STL	0.3084	6.5963	8.8378	0.2601	2.0231	3.7133	0.0507	5.4985	7.4936	-0.0720	1.7862	3.0337
	STL-R	0.6161	8.3938	14.5393	1.0596	3.1208	7.6671	0.2087	10.0203	17.7484	-0.1955	4.0311	9.6669
	DSA	-0.8544	6.5810	8.0764	-0.0890	1.3638	1.7137	0.1339	5.4249	6.9779	-0.0061	1.6214	2.0946
	DSA-R	-8.9126	14.6443	22.8953	-1.0741	2.7335	8.0703	0.5364	10.5313	19.4393	0.2499	3.3197	8.6444

Notes: **1** Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions, which have been calculated from the 2022 W01 to 2022 W52 vintages, with the 2024 W01 vintage being considered the final vintage. **2** The suffix “-R” indicates usage of robustness weights in the STL-based methods. **3** Bold figures indicate the smallest absolute value of the revision measure for the considered signal.

Table 7: Revision measures for signal estimates of the EC series

Signal	Method	PCE revisions (7)						P2P revisions (8)					
		$\{r_t\}$			$\{r_t(1)\}$			$\{r_t^\%\}$			$\{r_t^\%(1)\}$		
		MR	MAR	SD	MR	MAR	SD	MR	MAR	SD	MR	MAR	SD
DOW	AMB	−0.0045	0.2917	0.3734	−0.0027	0.1877	0.2518	0.0185	0.3783	0.4900	−0.0004	0.2354	0.3242
	X-11	−0.0065	0.4607	0.6115	−0.0057	0.2713	0.3917	0.0299	0.6658	0.9281	−0.0003	0.3867	0.5534
	STL	−0.0047	0.5138	0.6549	0.0007	0.2622	0.3474	0.0260	0.6514	0.8447	0.0014	0.3075	0.4149
	STL-R	0.0050	0.7328	1.0112	0.0092	0.2878	0.4918	0.0457	1.0680	1.5680	−0.0010	0.4020	0.7066
	DSA	0.0051	0.6669	0.8393	0.0024	0.3019	0.4500	0.0226	0.9173	1.1964	−0.0001	0.3823	0.5869
	DSA-R	−0.0017	0.7124	0.9937	0.0029	0.2718	0.4526	0.0483	1.0768	1.6450	0.0004	0.3812	0.6944
DOY	AMB	0.0994	0.2779	0.3371	−0.0017	0.2352	0.3150	0.0014	0.1095	0.1585	0.0007	0.0756	0.2006
	X-11	0.1427	0.8725	1.1046	0.0074	0.3011	0.5392	−0.0166	0.7465	1.0383	−0.0060	0.3715	0.6645
	STL	0.3100	0.8980	1.0969	0.0200	0.2451	0.4585	−0.0065	0.5967	0.7783	−0.0033	0.1604	0.3482
	STL-R	0.2228	1.1548	1.7485	−0.0166	0.3433	0.7985	−0.0121	1.1978	1.8280	0.0068	0.4401	0.9665
	DSA	0.2973	0.9974	1.2309	−0.0434	0.1787	0.2744	−0.0189	0.6968	0.9217	−0.0011	0.1524	0.2438
	DSA-R	0.2603	1.2816	1.9971	−0.0346	0.2089	0.3614	−0.0294	1.2518	2.2793	−0.0006	0.2436	0.4035
SA	AMB	−0.5252	3.9078	4.2480	−0.1137	0.4023	0.8586	−0.0350	0.9703	1.4044	−0.0043	0.2936	0.5648
	X-11	−0.5722	3.5372	3.9420	−0.1178	0.4563	0.9299	−0.0225	1.0715	1.5488	0.0018	0.4968	0.8716
	STL	−0.7415	3.5697	3.8884	−0.1376	0.3992	0.8884	−0.0316	0.8624	1.1885	−0.0025	0.2727	0.6089
	STL-R	−0.6345	3.7807	4.3506	−0.1035	0.5842	1.2071	−0.0363	1.7449	2.6238	−0.0113	0.6537	1.2384
	DSA	−0.0689	3.2118	3.5974	−0.0552	0.3648	0.7545	−0.0069	1.0330	1.5522	0.0010	0.2857	0.5181
	DSA-R	10.4909	10.8726	6.1892	−0.0994	2.3419	5.3962	−0.0229	2.1609	3.9668	0.0288	0.9762	3.1509

Notes: **1** Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions, which have been calculated from the 2022 W01 to 2022 W52 vintages, with the 2024 W01 vintage being considered the final vintage. **2** The suffix “-R” indicates usage of robustness weights in the STL-based methods. **3** Bold figures indicate the smallest absolute value of the revision measure for the considered signal.

Table 8: Revision measures for signal estimates of the PC series

Signal	Method	PCE revisions (7)						P2P revisions (8)					
		$\{r_t\}$			$\{r_t(1)\}$			$\{r_t^{\%}\}$			$\{r_t^{\%}(1)\}$		
		MR	MAR	SD	MR	MAR	SD	MR	MAR	SD	MR	MAR	SD
DOW	AMB	0.0763	2.2103	3.1339	0.0404	1.2419	1.6415	0.2836	3.1202	5.1228	-0.1347	1.8637	3.0456
	X-11	0.0949	2.7595	3.6672	0.0301	1.2649	1.6473	0.7260	3.8371	6.1208	-0.1073	2.0890	3.2502
	STL	0.0843	2.6994	3.5036	0.0208	0.9892	1.3494	0.1100	3.7226	5.7874	-0.1320	1.4958	2.4553
	STL-R	0.0909	2.8496	4.2793	0.0051	0.9608	1.2497	1.4255	4.7562	10.5106	-0.0423	1.4678	2.4099
	DSA	0.0931	3.6783	4.8995	-0.0156	1.2112	1.7643	0.0107	5.7176	9.0835	-0.1377	1.9265	3.4646
	DSA-R	0.0888	3.1465	4.4913	0.0025	1.0472	1.4083	1.6010	4.6903	10.3191	-0.0656	1.5985	2.8239
DOY	AMB	-0.3088	2.8611	4.3125	-0.0223	0.3626	0.4761	0.0615	0.3253	0.4338	-0.0003	0.1294	0.3127
	X-11	-1.0944	8.4631	9.9188	0.0970	1.3068	2.1997	-0.0252	4.2881	5.9206	-0.0241	1.5328	2.8865
	STL	1.8341	6.5753	8.4838	0.2848	0.6177	0.7779	0.3277	6.1507	8.2859	0.0003	0.7028	0.9071
	STL-R	-6.7880	13.2674	16.8933	-0.0704	1.0336	2.3371	-0.2422	13.8796	20.2565	-0.0465	1.3779	3.4765
	DSA	-11.3199	19.0658	18.7350	0.7219	1.2380	1.4820	0.0714	7.1447	10.0170	-0.0072	0.9584	1.4906
	DSA-R	-25.3005	32.9346	24.7989	0.0255	0.8056	1.3567	-0.2657	12.4715	17.5668	-0.0060	0.8501	1.7555
SA	AMB	1.6793	4.3459	5.1740	0.1377	1.3108	1.6515	0.2212	3.3550	4.7041	0.0053	1.4359	1.8891
	X-11	3.2601	8.8926	10.0633	0.0613	1.2799	2.1716	0.3177	5.0676	7.4760	-0.0683	1.1461	2.5721
	STL	-0.1045	5.2239	6.7513	-0.1634	0.4958	0.6284	-0.0731	4.9208	6.2597	-0.0080	0.5035	0.6847
	STL-R	12.2970	16.3781	21.7612	0.2716	1.3476	2.9981	-1.8190	13.3433	19.9030	-0.1165	1.6905	3.7127
	DSA	19.6083	25.8260	21.7179	-0.7027	1.4036	1.8680	0.1842	5.2320	6.7978	-0.0115	0.7401	1.2258
	DSA-R	189.3239	189.3239	133.2557	5.3566	12.5253	24.6638	-1.5283	12.7728	18.2027	0.0475	3.8231	11.2894

Notes: **1** Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions, which have been calculated from the 2022 W19 to 2022 W52 vintages, with the 2024 W01 vintage being considered the final vintage. **2** The suffix “-R” indicates usage of robustness weights in the STL-based methods. **3** Bold figures indicate the smallest absolute value of the revision measure for the considered signal.

Table 9: Revision measures for signal estimates of the TF series

Signal	Method	PCE revisions (7)						P2P revisions (8)					
		$\{r_t\}$			$\{r_t(1)\}$			$\{r_t^{\%}\}$			$\{r_t^{\%}(1)\}$		
		MR	MAR	SD	MR	MAR	SD	MR	MAR	SD	MR	MAR	SD
DOW	AMB	0.0015	0.4384	0.5433	0.0016	0.1990	0.2695	0.0029	0.5154	0.6692	0.0006	0.2548	0.3405
	X-11	0.0078	0.6436	0.8634	0.0077	0.4305	0.5689	0.0002	0.8517	1.1008	0.0005	0.6035	0.7801
	STL	0.0040	0.6913	0.8784	0.0008	0.3751	0.5176	−0.0009	0.8584	1.1210	−0.0018	0.4752	0.6328
	STL-R	0.0129	0.9421	1.2990	0.0063	0.5026	0.7483	0.0025	1.3469	1.8317	− 0.0002	0.7368	1.1041
	DSA	0.0028	0.8962	1.3703	− 0.0005	0.4518	0.6572	−0.0018	1.0649	1.6246	−0.0037	0.5350	0.7697
	DSA-R	0.0130	0.7975	1.0733	0.0031	0.3810	0.5176	−0.0126	1.0920	1.4438	−0.0035	0.5705	0.8004
DOY	AMB	0.0271	0.6848	0.7778	0.0011	0.1316	0.1718	0.0022	0.0373	0.0672	− 0.0005	0.0405	0.1070
	X-11	−0.0499	1.8493	2.3954	0.0505	0.6255	1.1504	−0.0253	1.4169	1.9633	−0.0045	0.7333	1.4028
	STL	0.0542	2.2346	2.9474	−0.0328	0.5115	1.1232	0.0352	1.5708	2.0482	0.0156	0.3305	0.6064
	STL-R	−1.6411	5.1987	6.5651	−0.0404	0.2573	0.4455	−0.0077	4.1142	5.6373	−0.0067	0.1429	0.3523
	DSA	−3.9899	4.3059	3.9323	−0.1287	0.3351	0.4484	0.0529	1.7401	2.3370	0.0017	0.3165	0.4560
	DSA-R	−5.0668	10.0134	12.3165	−0.4232	0.9035	1.4123	0.0691	3.9807	5.9361	0.0071	0.5036	0.9771
SA	AMB	− 0.0153	0.7978	0.9537	0.0006	0.2334	0.3132	− 0.0005	0.5220	0.6753	−0.0014	0.2541	0.3361
	X-11	0.1084	1.8441	2.4413	−0.0411	0.5882	1.1439	0.0155	1.4474	2.0535	−0.0076	0.6421	1.4390
	STL	0.0374	2.2437	2.9857	0.0483	0.4578	1.1250	−0.0318	1.4918	1.9481	−0.0151	0.2657	0.6292
	STL-R	2.1308	5.5131	6.9959	0.0440	0.5704	0.8656	−0.1715	4.1429	5.6881	−0.0026	0.7835	1.1595
	DSA	4.1072	4.9991	5.1034	−0.1650	0.5455	2.0886	−0.0652	1.6925	2.8091	0.0005	0.3069	1.2174
	DSA-R	7.4571	12.3056	16.0476	1.0067	1.5234	4.0021	−0.2665	4.0860	6.2392	0.0742	0.7636	1.8667

Notes: **1** Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions, which have been calculated from the 2022 W01 to 2022 W52 vintages, with the 2024 W01 vintage being considered the final vintage. **2** The suffix “-R” indicates usage of robustness weights in the STL-based methods. **3** Bold figures indicate the smallest absolute value of the revision measure for the considered signal.

Table 10: Revision measures for signal estimates of the TTMI series

Signal	Method	PCE revisions (7)						P2P revisions (8)					
		$\{r_t\}$			$\{r_t(1)\}$			$\{r_t^\%\}$			$\{r_t^\%(1)\}$		
		MR	MAR	SD	MR	MAR	SD	MR	MAR	SD	MR	MAR	SD
DOW	AMB	0.0195	1.4606	2.1984	0.0086	1.0303	1.6971	0.2699	3.6707	10.5069	0.5835	2.9175	11.2431
	X-11	0.0181	1.3287	2.1022	0.0002	0.6259	0.9508	-0.0109	2.7305	6.6669	0.1589	1.3857	3.6637
	STL	0.0219	1.7745	2.7460	0.0050	0.8294	1.3494	0.7172	4.4772	12.9571	0.4424	1.8836	7.3714
	STL-R	0.1108	2.3912	4.7985	0.0181	0.4306	1.6068	0.0814	2.8902	6.5829	0.0683	0.8990	2.7931
	DSA	0.3664	5.0294	7.5429	0.0392	2.1210	3.8612	-0.6775	15.9859	43.1123	-0.2424	6.9289	26.4939
	DSA-R	0.0816	1.9088	4.1741	0.0109	0.3765	1.5949	0.1988	2.3508	5.5251	0.0742	0.6624	2.3110
DOY	AMB	0.1111	0.8006	1.4221	0.0177	0.4557	0.8556	0.0125	0.6406	1.1404	-0.0263	0.3055	0.6840
	X-11	0.1270	0.6800	1.2489	0.0087	0.2023	0.4879	0.0074	0.6164	1.0589	-0.0192	0.2222	0.4502
	STL	0.0658	0.8022	1.4969	-0.0227	0.1782	0.6092	0.0087	0.9234	1.6362	-0.0277	0.1776	0.4574
	STL-R	0.0827	0.6642	1.8942	-0.0813	0.1705	0.9074	0.0059	0.9306	2.7806	-0.0198	0.2046	1.0114
	DSA	0.0589	1.4485	2.2582	0.0394	0.3481	0.6771	-0.0202	1.8700	2.8602	0.0052	0.4375	0.8329
	DSA-R	0.0959	0.4191	0.6201	-0.0317	0.0937	0.3698	0.0037	0.4308	0.8171	-0.0050	0.1402	0.5627
SA	AMB	0.0215	1.4787	2.1333	0.0247	0.9720	1.5527	-0.0102	1.5725	2.4688	0.0342	0.9999	1.7806
	X-11	0.0058	1.4092	2.2768	0.0218	0.5521	0.9163	-0.0452	1.7366	3.0652	-0.0082	0.7109	1.2562
	STL	0.0937	1.8512	2.7469	0.0560	0.6972	1.1375	-0.0841	2.2201	3.4592	-0.0074	0.7535	1.2661
	STL-R	0.1735	2.6855	5.4140	0.1190	0.5366	1.9238	-0.2327	3.6151	7.8962	-0.0386	0.6740	2.5656
	DSA	3.2011	5.9926	9.4187	0.2401	2.4847	4.7488	0.6713	7.0521	14.0862	-0.0586	2.4511	5.1080
	DSA-R	-1.0323	10.2205	12.3251	1.1241	7.4628	12.5132	-0.1559	4.1963	11.0910	0.2478	3.5045	12.5941

Notes: **1** Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions, which have been calculated from the 2022 W01 to 2022 W52 vintages, with the 2024 W01 vintage being considered the final vintage. **2** The suffix “-R” indicates usage of robustness weights in the STL-based methods. **3** Bold figures indicate the smallest absolute value of the revision measure for the considered signal.

- The mean (absolute) revisions are generally small for the DOW signals irrespective of both extraction method and implementation. As for the DOY and SA signals, however, they markedly deviate from zero for some extraction methods and series, indicating non-ignorable biases in initial estimates. This pattern is best seen in the mean final PCE revisions.
- The standard deviations of the revisions tend to be smallest for the DOW signal and highest for the SA signal for most extraction methods and series. Noteworthy exceptions are the PC and TTMI series for which, regardless of extraction method, the revisions in the DOW estimates are much more volatile than the revisions in the other two signal estimates, especially when looking at the P2P revisions.
- The extended AMB approach seems to produce the lowest and least volatile revisions in most signal estimates. Notable margins are recorded especially for the AP and TF series, bearing in mind that the unadjusted TF series is barely revised at all.
- The extended X-11 approach and the non-robust STL implementations also perform acceptably well for most series, producing quite similar revision measures in many cases.
- Despite a few good performances (e.g. for the DOY signal of the TTMI series), the robust STL estimates fall behind as they display some unacceptably high and volatile revisions in the longer DOY and SA signals.
- Both the non-robust and robust STL estimates obtained from JD+ tend to produce lower and less volatile revisions than their DSA counterparts.

Rounding out these findings, [Figure 8](#) shows for each series the convergence curve (9) of the lag- k PCE revisions in the DOW estimates obtained from the extended AMB and X-11 methods as well as from the non-robust DSA variant.⁷ The revisions converge within 5 weeks for the PC and TTMI series for all three extraction methods. The same speed is achieved for the AP series when DOW estimation is carried out with a non-parametric approach whereas the revisions in the AMB estimates show symptoms of convergence after 28–30 weeks, mirroring the classic trade-off between size of revisions and speed of convergence. Finally, convergence of revisions takes about 10–15 weeks for the EC and TF series for all three extraction methods.

4.3 Weekly Google trends

Unadjusted data In contrast to the daily WAI component series, the entire history of the GT series may be revised with the release of a new data vintage. Therefore, the relatively high revisions in the GT series come as no surprise; in particular, the lag-1 PCE and P2P revisions are noticeably larger than those of the daily WAI component series (see [Table 3](#)). These findings are somewhat in line with the opaqueness that often surrounds the publicly available information about Google’s data compilation and, consequently, with recent expressions of quality concerns about Google trends data (see e.g. [Cebrián and Domenech, 2023, 2024; Fenga, 2020](#)).

⁷The convergence curves for the DOY and SA signals were also checked but turned out to evolve much more erratically. Due to this lack of clarity, they are not shown here.

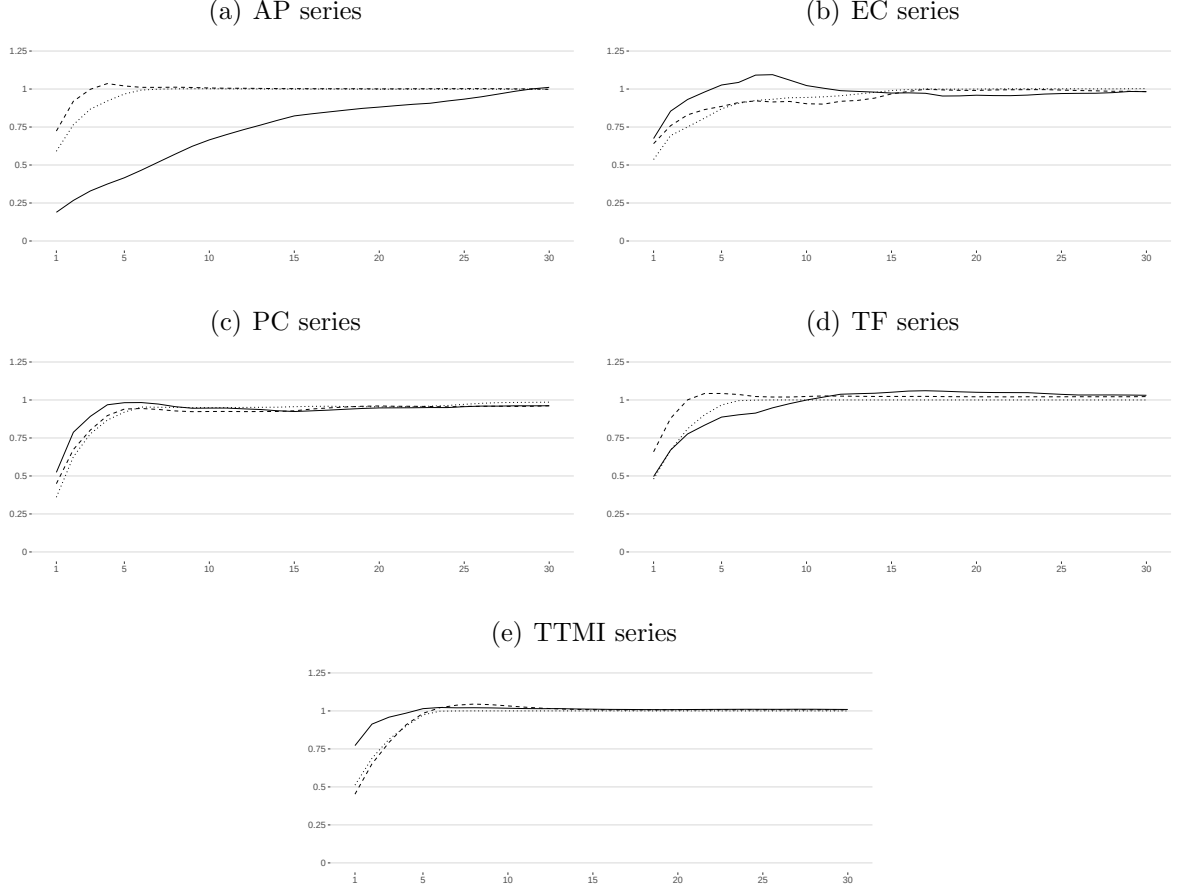


Figure 8: Rate of convergence (9) with $k \in \{1, \dots, 30\}$ for the DOW estimates obtained from the extended AMB (*solid line*) and X-11 (*dashed line*) methods and from the non-robust DSA variant (*dotted line*).

Pretreatment Figure 9 visualises the cross-vintage stability of the parameter estimates and their point-wise standard errors obtained from model (5). In general, it seems that there is an initial 10-vintage phase of marked changes followed by a longer period of relative stabilisation. Hence, at first glance, the estimated holiday effects shown in Panels (a)–(g) appear to evolve more erratically across vintages than those shown in Figure 3 through Figure 7 for the daily WAI component series. But this is just an optical illusion due to a finer scale of the vertical axis; in fact, recalling Table 4, they are of similar stability as indicated by their cross-vintage standard deviations that range between 0.0035 (Carnival) and 0.0061 (Christmas). In contrast, the estimated MA parameters shown in Panels (h)–(i) indeed fluctuate somewhat stronger than the estimates obtained for the daily WAI component series; more precisely, their cross-vintage standard deviations are given by 0.0415 for $\hat{\theta}_1$ and 0.0418 for $\hat{\theta}_{52.18}$. Similar comments apply to the point-wise standard errors.

Complementing the descriptive outlier statistics reported in Table 5, it is finally noted that the number of automatically detected outliers varies between 0 and 7 across all vintages, with average and standard deviation being 2.51 and 1.41, respectively.

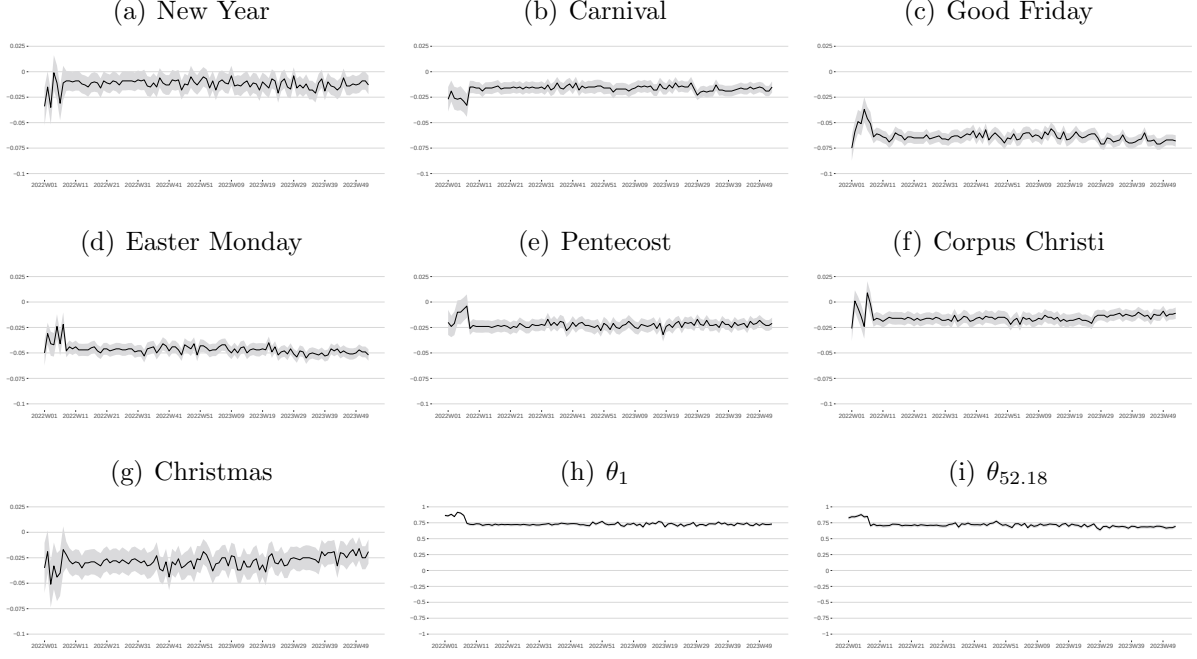


Figure 9: Estimated holiday effects and MA parameters from (5) for the GT series. Shaded areas mark point-wise ± 1 SE intervals.

Signal estimates Table 11 reports the revision measures for the concurrent estimates of the WOY pattern and the seasonally adjusted GT series. These measures are generally low for either signal and very similar across the JD+ methods. Nevertheless, the lowest and least volatile revisions in the WOY pattern are often produced by the extended AMB approach yet again, followed by the extended X-11 method. In contrast, somewhat mixed results are obtained for the SA signal. The extended AMB and X-11 approaches are still competitive; however, the non-robust STL method produces the smallest measures for the lag-1 PCE revisions whereas the robust STL method gains a slight advantage in terms of low lag-1 P2P revisions. Interestingly, the mean PCE revisions indicate that for each method the initial SA estimates are slightly corrected upwards after one week but largely revised downwards in the end. Overall, the average size and volatility of the revisions in the concurrent estimates of the seasonally adjusted GT series are very similar to those of the unadjusted GT series (see Table 3).

4.4 Cautionary remarks

Sub-weekly revisions in unadjusted daily data As mentioned at the beginning of Section 2, each weekly Bundesbank vintage contains seven new observations on average for the daily series. Therefore, each of those new observations (except the last one) might have already been subject to prior daily or other sub-weekly revisions made by the original data provider; the Bundesbank vintages essentially cover the weekly net effects of these sub-weekly data revisions and hence tend to display more data revisions towards their ends. For that reason, slightly different results might be obtained for the daily data when rerunning the present study with the sub-weekly vintages of the original data providers.

Table 11: Revision measures for signal estimates of the GT series

Signal	Method	PCE revisions (7)						P2P revisions (8)					
		$\{r_t\}$			$\{r_t(1)\}$			$\{r_t^{\%}\}$			$\{r_t^{\%}(1)\}$		
		MR	MAR	SD	MR	MAR	SD	MR	MAR	SD	MR	MAR	SD
WOY	AMB	-0.4388	0.7823	0.8190	-0.3734	0.4663	0.3966	0.0007	0.7418	0.9550	-0.0152	0.3379	0.5093
	X-11	-0.2073	0.6962	0.8483	-0.1986	0.5044	0.6820	0.0231	0.7838	0.9976	-0.0091	0.7385	0.9593
	STL	-0.3952	0.7884	0.9457	-0.3865	0.4811	0.4545	0.0683	0.9033	1.2708	0.0037	0.4159	0.6043
	STL-R	-0.4069	0.7913	0.9542	-0.2981	0.4709	0.5337	0.0711	0.9718	1.4162	0.0005	0.5674	0.7580
SA	AMB	4.0205	4.0205	2.1533	-0.9727	1.5745	1.8987	0.0116	1.9282	2.7060	0.1104	1.8977	3.0305
	X-11	3.7805	3.7882	2.1955	-1.1409	1.7636	2.0919	-0.0170	1.9686	2.7270	0.1060	2.1551	3.3152
	STL	3.9765	3.9814	2.1702	-0.9600	1.5540	1.8705	-0.0487	1.9948	2.6436	0.0992	1.9093	3.0325
	STL-R	3.9927	4.0106	2.3508	-1.0461	1.6680	1.9377	-0.0652	2.0199	2.6779	0.0936	1.9553	3.0241

Notes: **1** Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions, which have been calculated from the 2022 W01 to 2022 W52 vintages, with the 2024 W01 vintage being considered the final vintage. **2** The suffix “-R” indicates usage of robustness weights in the STL method. **3** Bold figures indicate the smallest absolute value of the revision measure for the considered signal.

Asymmetric signal extraction filters Ideally, the final signal estimates should be obtained from a sub-span of the final data vintage $\mathbf{v}_T$ that has been chosen such that only symmetric signal extraction filters can be applied. This is in fact the case for the final DOW estimates in our revision analysis; however, the final DOY/WOY and SA estimates for the series with a relatively short sample span might be affected by bias-variance trade-offs and/or phase shifts introduced through the application of asymmetric signal extraction filters near the sample boundaries. In these cases, relatively short seasonal filters are often specified in the non-parametric methods to compensate for limited data availability (see [Appendix B](#)). As a result, leakage of the aforementioned undesired effects should not pose a problem for the PC and TF series from which, for example, the DOY pattern is extracted with the short 3×1 seasonal filter in X-11; it should also be no source of major concern for the AP and EC series for which DOY extraction is carried out with the relatively short 3×3 seasonal filter. However, presence of such leakage effects cannot be ruled out completely for the TTMI and GT series as DOY/WOY extraction utilises the relatively longer 3×5 and 3×9 seasonal filters, respectively. Overall, it seems fair to say that for some series the final PCE and P2P revisions have been calculated from “nearly final” signal estimates in our analysis.

Quality diagnostics Standard quality diagnostics have been consulted to set up both pretreatment model (5) and the seasonal adjustment specification for each WAI component series using the unadjusted data released in the 2022 W01 vintage (see [Appendix B](#) for details). In practice, those diagnostics would typically also be looked at when validating, or further calibrating, the initial specification with later data releases. These regular checks, however, are not performed here; instead, the initial specification is kept fixed across all vintages for the sake of retaining tractability, in line with other large-scale analyses of real-time revision profiles.

Nevertheless, we can still perform a final overall check for systematic seasonal adjustment inadequacy across the 2022 W01 through 2024 W01 vintages. To this end, we calculate the sample first-order seasonal autocorrelation, say $\hat{\rho}_\tau$, of the seasonally adjusted series from each data vintage and a kernel-based density estimate from the resulting 105 realisations of $\hat{\rho}_\tau$. This estimated density should ideally have most of its mass centred closely around zero ($\hat{\rho}_\tau = 0$); significant mass shifts to the left or right, however, indicate systematic over-adjustment ($\hat{\rho}_\tau < 0$) and under-adjustment alias residual seasonality ($\hat{\rho}_\tau > 0$), respectively. Utilising the Epanechnikov kernel, [Figure 10](#) reveals minor symptoms of residual DOW dynamics in the seasonally adjusted AMB and X-11 estimates for some daily WAI component series and somewhat larger symptoms in the non-robust DSA estimates of the EC and TTMI series. Inadequacies with respect to DOY and WOY seasonality, however, seem for each method to tilt more towards over-adjustment, which is often regarded the less severe issue. Overall, the systematic inadequacies witnessed here are not dramatic in general and, in most cases, least pronounced for the extended AMB approach. Hence, they could be seen rather as a gentle invitation to fine-tune the specifications of the non-parametric seasonal adjustment methods further and, in particular, to revise the selected STL and X-11 filters in the future. This would also agree with the conclusion one might draw from the high revision measures recorded for some signal estimates obtained with the robust STL method (see especially the high revisions in the estimated DOY and SA signals for the relatively short PC series reported in [Table 8](#)).

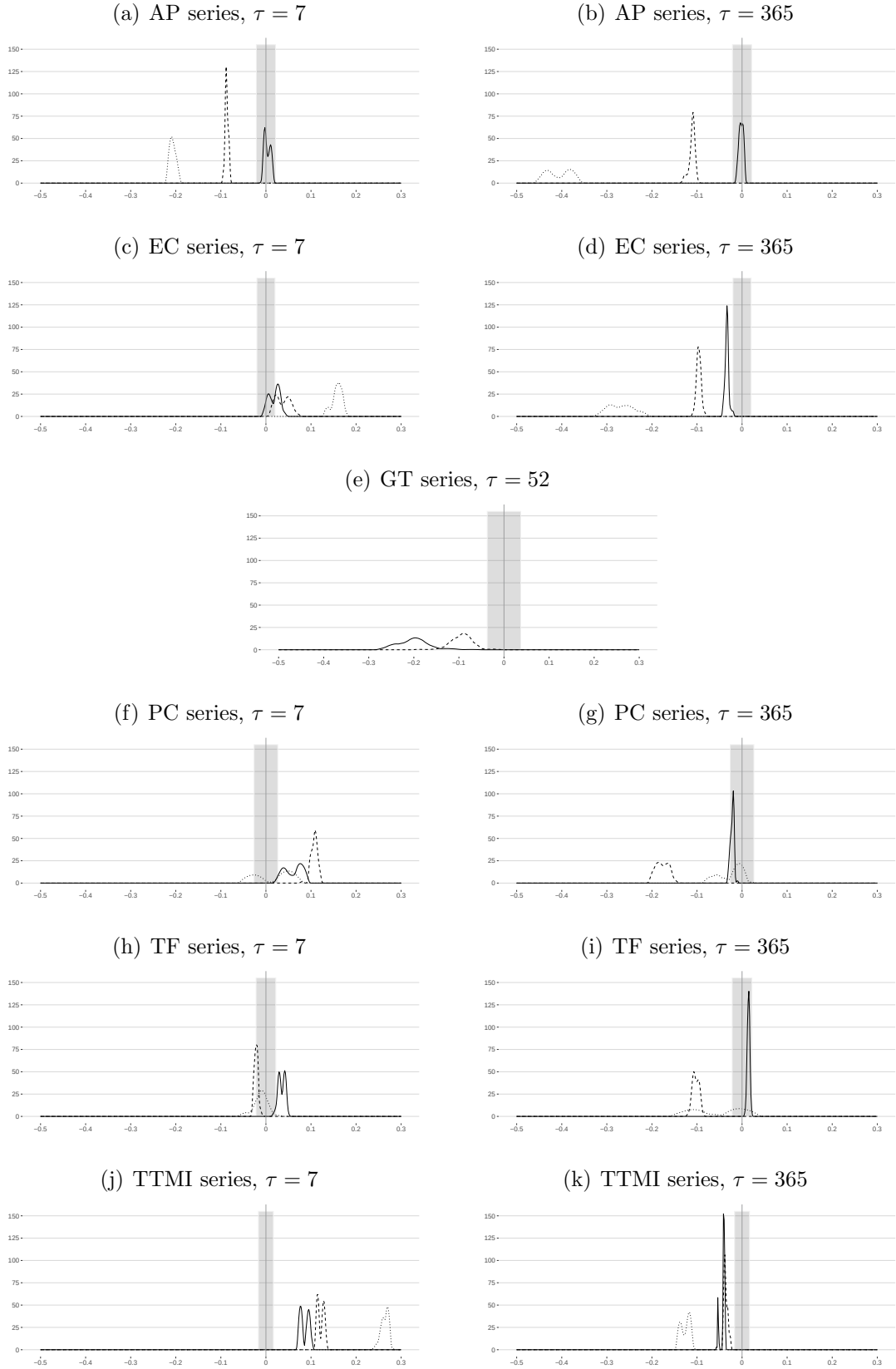


Figure 10: Epanechnikov kernel density estimates for $\hat{\rho}_\tau$ obtained from the differenced logged seasonally adjusted WAI component series using the extended AMB (*solid line*) and X-11 (*dashed line*) methods and the non-robust DSA variant (*dotted line*). Shaded areas mark ± 1 Bartlett approximation to the large-lag SE of $\hat{\rho}_\tau$.

Table 12: DSA estimates of the holiday component in (1) at no-holiday days

Robustness weights	Vintage	AP	EC	PC	TF	TTMI
No	First	1.0036	1.0023	1.0090	1.0022	1.0264
	2024 W01	1.0036	1.0021	1.0092	1.0021	1.0258
Yes	First	1.0042	1.0032	1.0118	1.0032	1.0337
	2024 W01	1.0041	1.0030	1.0121	1.0030	1.0326

Note: The first vintage is the 2022 W19 vintage for the PC series and the 2022 W01 vintage for the other series.

Estimated holiday component in DSA Borrowing notations from model (5), the holiday component at time t is naturally estimated as $\hat{h}_t = f^{-1}(\mathbf{x}_{t,h}^\top \hat{\boldsymbol{\beta}}_h)$ where $\mathbf{x}_{t,h}$ is the sub-vector of $\mathbf{x}_t$ that contains only the holiday-related exogenous variables and $\boldsymbol{\beta}_h$ is the corresponding sub-vector of $\boldsymbol{\beta}$. Hence, when no holidays occur at t (meaning $\mathbf{x}_{t,h} = \mathbf{0}$), we expect $\hat{h}_t = 0$ in the additive version of (1) and $\hat{h}_t = 1$ in the multiplicative version. This requirement is met when estimating $\{h_t\}$ from model (5) in JD+; in DSA, however, a slight yet constant bias is introduced so that in the absence of holidays the estimated holiday component never equals the neutral element of the UC decomposition (1), that is $\hat{h}_t = c_h \notin \{0, 1\}$. Table 12 exemplarily reports the values of c_h recorded for the multiplicative models of the five daily WAI component series as released in the first and last data vintages. It is seen that these values are always larger than one—indicating an unwarranted downward correction—, change gradually across vintages and are slightly larger when robustness weights are used (for DOW estimation). Although these distortions are clearly unsatisfactory from a theoretical standpoint, they exhibit little cross-vintage variation and hence should not introduce severe biases in the revision measures for the DSA estimates of the DOY and SA signals.

5 Summary

Recent theoretical advances in the modelling and seasonal adjustment of infra-monthly time series have sparked interest in empirical evaluations of those new methods. Using real-time data of selected daily and weekly seasonal time series relevant for the calculation of the weekly activity index (WAI) for the German economy, the present paper contributes to this research strand by assessing the cross-vintage stability of estimated holiday-related deterministic pretreatment effects and the revision profiles of various signal estimates obtained with tailored methods, such as generalisations of the popular ARIMA model-based (AMB) and X-11 seasonal adjustment approaches implemented in a recent release of the JDemetra+ (JD+) time series software for official statistics. The performance of these methods is also compared with that of the STL-based DSA approach that is currently in use for running experimental seasonal adjustments of the daily WAI component series.

There are three key findings. First, the tailored JD+ methods—and especially the pretreatment routine including automatic outlier detection—were often noticeably faster than the DSA approach. Second, the JD+ and DSA linearisation steps produced parameter estimates of similar cross-vintage stability even in cases of different outcomes

regarding automatic outlier detection. Third, there is no universally dominant method in terms of low revisions; nevertheless, the extended AMB approach tended, on average, to generate lower and less volatile revisions in various concurrent signal estimates than any other method considered at the occasional expense of slower convergence of revisions (which was observed for the day-of-the-week signal in one out of the five daily WAI component series). The extended X-11 approach and the non-robust STL implementations also provided acceptable results in many cases. The robust STL implementations, however, produced unacceptably high and volatile revisions in the estimated day-of-the-year pattern and in the seasonally adjusted figures of some daily series, signalling inadequate adjustments (a phenomenon that has already been documented in [Gray and Thomson, 1990](#)).

The present real-time revision analysis can be extended in multiple ways. For example, considering additional data-specific holiday variables could foster more nuanced pretreatment models; in this regard, implementing standard errors that are robust against residual autocorrelation and/or heteroskedasticity could improve the quantification of parameter uncertainty. Additional benefits could also be gained from further customising signal extraction with the tailored JD+ methods. The extended X-11 approach, for instance, implements a wide range of options for kernel-based trend-cycle extraction ([Proietti and Luati, 2008](#); [Quartier-la-Tente, 2024](#)) while the extended AMB approach enables not only sequential but also simultaneous extraction of the seasonal patterns in (2). As regards STL, mixed usage of robustness weights for daily data, that is running robust STL when extracting the day-of-the-week pattern and non-robust STL when extracting the day-of-the-year pattern, could be explored.

The focus of the revision analysis could also be shifted from the present real-time perspective to an isolated assessment of technical (filtering) revisions that are caused merely through the addition of new observations, as data revisions turned out here to contribute in a minor way to revisions in seasonally adjusted estimates. To this end, a quasi-real-time study or a sliding-spans analysis in the sense of [Findley, Monsell, Shulman, and Pugh \(1990\)](#) could be conducted, elaborating our findings for the daily total flights series. The attention could also be changed from analysing revision profiles of concurrent signal estimates, which utilises (fully) asymmetric filters, to exploring the potential benefits of using projected seasonal factors, which requires forecast extensions for the unadjusted data that in turn have long been known to have reductive effects on revisions ([Cleveland, 1983](#)). Finally, the tailored JD+ methods could be compared with structural time series models or other elaborate seasonal adjustment approaches not considered here (see e.g. [Webel, 2022](#), for an overview).

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Appendix

A Conceptual differences between the DSA and JD+ approaches

There are three key conceptual differences between the STL-based seasonal adjustment approach for daily data implemented in the `{dsa}` package (Ollech, 2021) and the JD+ methods that are applicable to time series of any seasonal periodicity (see Webel and Smyk, 2024, for a detailed description).

Order of sequential signal extraction The DSA approach starts with an extraction of the DOW pattern from the unadjusted data. In a second step, the DOW-adjusted data is corrected for outliers and other deterministic effects, such as holiday-related ones, using a linear time series regression model that is similar to (3) and (5). In a third step, the day-of-the-month (DOM) pattern is extracted from the linearised DOW-adjusted data. Finally, the DOY pattern is extracted from the remainder. Although each of these four steps can be optionally skipped, the above order is mandatory in the DSA approach.

In contrast, signal extraction with any JD+ method can be arranged in any order. Throughout this paper, we stick to the classic order, that is we start with data pretreatment using model (5); afterwards, the DOW pattern is extracted from the linearised data, which is followed by the extraction of the DOM and DOY patterns in the aforementioned DSA order. Therefore, when interpreting our results, one should keep in mind that the DSA estimates of the holiday component $\{h_t\}$ in (1) and of the DOW pattern $\{s_t^{(7)}\}$ in (2) will most likely contain some dynamics that are intentionally not present in the corresponding estimates obtained from any JD+ method, and vice versa.

Modelling seasonality in data linearisation In DSA, the time series regression model for the linearisation of the DOW-adjusted data contains as exogenous variables a user-specified number of Fourier terms evaluated at the DOY harmonics to capture DOM/DOY-related dynamics. The residuals of this model are assumed to follow a non-seasonal ARIMA model. In contrast, the JD+ pretreatment models (3) and (5) rely on a stochastic Airline-type representation of the seasonal movements in the regression disturbances, which is often more parsimonious than the deterministic DSA framework.

Handling fractional periodicities In DSA, the fractional periodicities of the DOM and DOY patterns—30.4369 and 365.2425, respectively—are temporarily made integers through data regularisation. More specifically, the DOM extraction step begins by stretching each month to 31 days where the artificial observations for missing days are obtained as cubic spline interpolations. Similarly, the DOY extraction step begins by dropping all observations recorded on 29 February, treating each year as if it had 365 days; the resulting missing values in the final estimates of the DOY pattern and the seasonally adjusted data are interpolated with cubic splines yet again. In JD+, however, the extended AMB and X-11 methods utilise the first-order Taylor approximation (4) to handle fractional periodicities, whereas the STL implementation automatically rounds down each seasonal periodicity to its nearest integer.

Either concept has merits and demerits. The weighted averaging principle (4) always captures the exact seasonal frequencies but sacrifices the unit-root properties of the seasonal summation operator (6) whenever $\alpha_\tau > 0$, which has consequences for the extended AMB and X-11 approaches. As regards the AMB method, any seasonal pattern whose (derived) component ARIMA model contains (6) as a factor will be stationary; as regards the X-11 method, the resulting seasonal filters will compromise some extraction power at the higher seasonal harmonics. Temporary data regularisation, on the other side, enables the application of seasonal filters that possess high extraction power at all seasonal frequencies. However, the squared gains of these filters will display peaks that are not located at the exact seasonal frequencies, especially for the higher harmonics.

B Seasonal adjustment specifications

The calibration of the seasonal adjustment specification for each WAI component series is based upon the unadjusted data released in the 2022 W01 vintage. Once completed, each specification is held fixed over all subsequent data vintages. It should be noted that our large-scale analysis will involve some pragmatic choices with respect to building pretreatment model (5); however, more nuanced models may be warranted for other types of analyses especially when the focus is on capturing particular data subtleties at specific points in time. Given the relatively short sample span of most WAI component series, estimation of such subtle effects is usually difficult due to the low number of observed cases, so our pragmatic choices seem sufficient for the time being.

Type of UC model The choice between the additive or multiplicative version of UC model (1) is based upon a set of commonly accepted model selection criteria calculated from pretreatment model (5) as specified below. The results reported in Table 13 indicate that the multiplicative UC model is preferred for each WAI component series.

Pretreatment A common set of user-defined dummy regression variables is considered in model (5) to estimate the effects of selected fixed and moving holidays for the daily WAI component series. The fixed holidays are New Year’s Day (1 January), Epiphany (6 January), Labour Day (1 May), German Unification Day (3 October), the 500-th Reformation Day (31 October 2017), All Saints’ Day (1 November), Christmas Eve (24 December), Christmas Day (25 December), Boxing Day (26 December) and New Year’s

Table 13: Model selection criteria for the daily and weekly WAI component series

Series	UC model (1)	AIC	AICC	BIC	HQ
AP	Additive	12,109.54	12,109.97	12,229.03	12,153.22
	Multiplicative	9,574.50	9,575.06	9,695.66	9,619.20
EC	Additive	24,460.87	24,461.61	24,636.17	24,524.45
	Multiplicative	19,215.90	19,216.82	19,392.24	19,280.36
GT	Additive	6,503.52	6,503.85	6,561.63	6,525.67
	Multiplicative	5,866.09	5,866.51	5,928.32	5,889.88
PC	Additive	12,212.23	12,213.31	12,347.35	12,262.86
	Multiplicative	7,744.06	7,746.18	7,895.26	7,801.61
TF	Additive	41,321.85	41,322.60	41,473.94	41,377.61
	Multiplicative	32,967.94	32,968.84	33,114.77	33,022.29
TTMI	Additive	31,513.84	31,515.81	31,971.53	31,674.08
	Multiplicative	27,887.28	27,889.93	28,391.49	28,064.48

Notes: **1** The considered criteria are Akaike’s information criterion (AIC), the corrected AIC (AICC), the Bayesian information criterion (BIC) and the Hannan-Quinn criterion (HQ). **2** For multiplicative UC models, the criteria are defined in terms of the untransformed data, that is the maximised log likelihood obtained from the differenced logged data is corrected using the Jacobian log transformation adjustment.

Eve (31 December). Fixed holidays that fall onto a Sunday are treated as regular Sundays except for the TF series. The moving holidays are Good Friday, Easter Monday, Ascension, Ascension Friday, Pentecost Monday, Corpus Christi and Corpus Christi Friday. The corresponding regression variables have been corrected for their long-term means calculated from 1 January 1950 to 31 December 2030 to avoid confounding with annual seasonality. There are three exceptions to this design: first, the 500-th Reformation Day is not considered for the PC series since the event happened before the beginning of the sample span; second, only the five dummy variables related to New Year and Christmas are considered for the TF series along with four additional dummy variables for selected U.S. federal holidays (Easter Sunday, Independence Day, Thanksgiving, Thanksgiving Friday); third, two additional dummy variables covering the start and end of daylight saving time (DST) are considered for the EC series. In addition, automatic detection of additive outliers and level shifts with length-adjusted critical t -values based upon the U.S. Census Bureau’s modifications to the original formula derived in [Ljung \(1993\)](#) is run for each series. The same setup is used in the DSA approach, noting that in practice the experimental seasonal adjustments of the daily WAI component series often utilise much higher critical t -values for automatic outlier detection.

The visual evidence provided in [Figure 1](#) and [Figure 2](#) suggests the presence of strong day-of-the-week (DOW) and day-of-the-year (DOY) patterns in each daily WAI component series. Therefore, we set $\mathbb{S} = \{7, 365.2425\}$ in (2) and (5), along with $d = 2$ in the latter equation.⁸ In DSA, seasonality in the linearisation step is modelled with a set

⁸Following [Webel and Smyk \(2024\)](#), the choice of $d = 2$ has been mainly motivated by pairwise compar-

of 20 Fourier terms plus—for the sake of consistency with (5)—a (011) specification for the orders of the non-seasonal ARIMA model driving the regression residuals. No forecasts are generated from either linearisation model; this intentionally takes a MINIMAX perspective as we seek the seasonal adjustment method that amongst all competitors generates minimal revisions (on average) in signal estimates under maximally inconvenient circumstances.

For the weekly GT series, two types of weekly user-defined holiday regression variables are considered in (5), where weeks are counted according to the U.S. CDC version of an epidemiological (EPI) week: first, dummy variables are used to capture the effects related to Carnival, Good Friday, Easter Monday, Pentecost and Corpus Christi; second, weekly shares of k -day periods are used to capture the effects of those holidays that are spread across k consecutive days and hence may be distributed across two adjacent weeks in some years. In particular, we have $k = 3$ for the Christmas period and $k = 2$ for the New Year period, whereby holidays that fall onto a Sunday are always counted as holidays. Long-term means are removed from all weekly regression variables, noting that even holidays with a fixed datum are moving on the weekly scale. For example, each fixed holiday of the 3-day Christmas period can fall in either EPI week 51 or 52. In addition, automatic outlier detection is run in the exact same way as for the daily WAI component series. Based upon spectral evidence (Figure 2), stochastic seasonality in model (5) is captured through a single week-of-the-year (WOY) pattern, that is through setting $\mathbb{S} = \{52.18\}$ and again $d = 2$.

Signal extraction The sequential extraction of the DOW and DOY patterns from the (linearised) daily WAI component series is carried out with the following specifications:

- The extended AMB approach is run in full default mode without calculating back- and forecasts of any estimated signal. Asymmetric Wiener-Kolmogorov filters are therefore applied automatically near the sample boundaries.
- The extended X-11 approach is run with trend-cycle filters constructed from a cubic Henderson kernel. The length of the symmetric filter is always set to the smallest odd integer larger than the seasonal periodicity, that is the length is 9 for DOW extraction and 367 for DOY extraction. Asymmetric variants are obtained through the cut-and-normalise approach (Gasser and Müller, 1979). As for the seasonal filters, the 3×9 filter is chosen for DOW extraction from each series. For DOY extraction, however, the maximum length of the seasonal filters is dictated by the number of observations available in the 2022 W01 vintage (Table 1). Therefore, the chosen seasonal filters are 3×9 for the TTMI series, 3×3 for the AP and EC series and 3×1 for the PC and TF series, bearing in mind that seasonal adjustment of the PC series has to start with the 2022 W19 vintage since earlier vintages are too short even for applying the 3×1 filter. It should also be noted that the extended X-11 method does not generate naive forecasts of any seasonal pattern; as a result, asymmetric trend-cycle and seasonal extraction filters are used near the beginning and end of the series. Finally, the default σ -limits of (1.5, 2.5) are specified for the automatic detection of extreme values in the detrended data.

isons between model-based trend-cycle estimates and out-of-sample forecasts obtained from model (5) with $d \in \{1, 2, 3\}$.

- The STL method in JD+ is run with trend-cycle and seasonal LOESS smoothers whose lengths match the lengths of their X-11 counterparts, regardless of whether the non-robust or robust STL variant is applied.
- The DSA approach is run with the same trend-cycle and seasonal LOESS smoothers specified in the JD+ implementation of STL. In addition, the “combined factors” option is selected to interpolate the seasonally adjusted values on 29 Februaries.

The extraction of the single WOY pattern from the linearised weekly GT series is generally based upon the same setup for each JD+ method. The only slight exception is the length of the symmetric X-11 trend-cycle filter, which is set to 55 in place of 53 alongside the 3×5 seasonal filter.